Design in the Modern Age: Investigating the Role of Complexity in the Performance of Collaborative Engineering Design Teams

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ABSTRACT

The world of engineering design finds itself at a crossroads. The technical and scientifically rooted tools that propelled humankind into the modern age are now insufficient as evidenced by a growing number of failures to meet design expectations and to deliver value for users and society in general. In the empirical world, a growing consensus amongst many design practitioners has emerged that engineering design efforts are becoming too unmanageable and too complex for existing design management systems and tools. One of the key difficulties of engineering design is the coordination and management of the underlying collaboration processes. Development efforts that focus on the design of complex artefacts, such as a satellite or information system, commonly require the interaction of hundreds to thousands of different disciplines. What makes these efforts and the related collaboration processes complex from the perspective of many practitioners is the strong degree of interdependency between design decision-making occurring, often concurrently, across multiple designers who commonly reside in different organizational settings. Not only must a design account for and satisfice these dependencies, but it must remain also acceptable to all design participants. Design in effect represents a coevolution between the problem definition and solution, with a finalized design approach arising not from a repeatable series of mathematical optimizations but rather through the collective socio-technical design activities of a large collaboration of designers. Despite the importance of understanding design as a socio-technical decision-making entity, many of the existing design approaches ignore socio-technical issues and often view them as either too imprecise or too difficult to consider. This research provides a performance measurement framework to explore these factors by investigating design as a socio-technical complex adaptive collaborative process between the designer, artefact, and user (DAU). The research implements this framework through an agent-based model, the Complex Adaptive Performance Evaluation Method for Collaboration Design (C^2D). This approach allows a design management analyst to generate insights about potential design strategies and mechanisms as they relate to design complexity by examining the simulated performance of a design collaboration as it explores theoretical design fitness landscapes with various degrees of ruggedness.

To my friends, teachers, mentors, and those who had no choice…

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Foreword

Over the past century, the application of technical, scientific, and mathematical rigor has steadily advanced the overall body of engineering design theory and its practice. In the modern age, this progression of technical expertise has enabled contemporary designers to create a vast array of elaborate and often complex engineered systems and devices that we refer to as engineering artefacts. This work uses the term complex and complexity to denote a system with multiple interconnected and interdependent design elements whose combined interactions can give rise to system effects, including sometimes-unanticipated system behaviors. Modern engineered systems are commonly themselves complex adaptive systems exhibiting, in the words of Holland (1998), 'perpetual novelty' or the ability to behave and respond in continually new and unexpected ways. For the consummate scientist and engineer, the resulting uncertainties posited by these complex systems represent obstacles to creating simple and precise models of a system rooted in the natural laws governing a physical system. This discomfort with the messy realisms of engineering design and its socio-technical actualities has led to the development of a series of reductionist tools and procedures for engineers, including mathematical formalisms for incorporating randomness in design through statistical and stochastic processes (Haugen 1980; Sidall 1984).

As a result, most of the existing models of design are mechanical, overly constrained, and neglect the capacity and impact of having multiple decision-makers working together who jointly perceive, decipher, and respond to interacting and often competing design goals and objectives. As systems increase in their complexity, the goal of managing uncertainty must shift from a dependence on overly rigid design models to more appropriate design models that embrace the complex subtleties of the real world and the limitations they impose on the designer's decision-making processes. The necessity to better understand and model the design process arises in part from the growing number of engineering development efforts that fail to meet design objectives and miss value expectations (Eason 2001). To overcome these limitations, new approaches for design are required that allow for the continuous innovation and development of artefacts. These new approaches must find ways to effectively respond to increasingly difficult social and technological challenges, while minimizing development times, maintaining safety, and incentivizing resiliency, *i.e.* the ability of a system to recover and operate through unexpected events.

This research asserts that a future approach requires a representation of design that encompasses the team-based nature of design and the role of collaboration in real-world design activities. It does so based on empirical and personal observations that the success or failure of any complex design activity, one commonly linking hundreds to even thousands of engineers, follows foremost from the ability of designers to work together in complex socio-technical environments. By adopting a socio-technical view of design, this research provides a holistic framework from which to explore the role of structural design complexity (i.e. the complexity arising from the mapping of design parameters to functional requirements) and the dynamics of design-teams. The research implements this framework by representing the designer, artefact, and user (DAU) as a complex adaptive system exploring a theoretical design fitness landscape that corresponds conceptually to how well a design satisfices the underlying design requirements. Specifically the Complex Adaptive Performance Evaluation Method for Collaborative Design (C^2D) includes the following:

i. Construct the simulation environment in NetLogo modelling software to represent design complexity – the research represents the complexity of design through the construction of a design landscape using an approximated NK landscape generation procedure after Kauffman (1989) commonly used due to its ability to relate the size (N) and interdependency (K) of an entity; and,

   a. This design landscape simulates all possible design fitness values for all possible design configurations based on the number of interactions K between requirements and the number of requirements N of a design. In this procedure, each location on the design landscape corresponds to a varying height that represents its degree of fitness. Neighboring points on this landscape become increasingly uncorrelated as the degree of interdependency K increases, which in turn leads to an increasingly rugged landscape with diverse topological figures, such as peaks and valleys. In maximally rugged landscapes where $K = N - 1$, points on the landscape remain entirely uncorrelated resulting in a landscape where all points take on separate random fitness values.

   b. A key conceptual element of the C^2D framework is that each individual location on the design landscape corresponds to a different potential design approach. More specifically, each point on the design landscape represents a different design concept with its own new configuration of design parameters used in satisficing the requirements of a design. Design agents must search out this space balancing the need for finding a good design (sufficient fitness) against the need to minimize the amount of time spent searching through the design landscape.

ii. Implement the design-team and the DAU collaboration in the simulated environment of the NetLogo model – the research examines the design process through the perspective of design teams and their collaboration through an agent-based model where each individual agent (i.e. an actor in the model) conceptually represents a designer. These agent-based designers follows a simple set of rules governing their actions. Additionally, these agent-based designers work as part of a team and are engaged in an overall collaboration that explores the constructed design landscape in search of fitness. The key components of these teams and the DAU collaboration include:

   a. Individual agent-based designers follow a series of rules that govern their decision-making. For example, each individual agent follows a rational basis of decision making (i.e. agents only move on the landscape when it improves their individual fitness). Poor design solutions are eventually eliminated in the simulation through a process that mimics natural selection or evolution in nature, *i.e.* fitter solutions tend to be more successful in competing for resources and for recruiting newcomers in the formation of teams.

   b. Design teams are formed in C^2D sequentially to solve the individual design problems (although future research includes the possibility of introducing multiple design teams simultaneously to represent concurrent design). As the team members on the design team change, a large group of past and future collaborators emerges. Because of their previous labors, this collaboration network offers expertise and backgrounds relevant to the design problem in hand. In effect, this larger DAU collaboration represents a support network for design-teams to tap. Design teams bring in expertise by reengaging a previous team member and adding them to the design team or they bring in newcomers as described below.

   c. Design teams formed in the model use the procedures and team-formation parameters identified as highly explanatory for collaborations by Guimerà, Uzzi, Spiro, and Amaral (2005). These team-formation dynamics give rise to a complex DAU collaboration network over the course of a simulation; these networks arise out of a few simple parameter values. These identified parameters adopted and added in the C^2D model include:

i. the likelihood of incorporating a newcomer,

   1. This parameter represents the need or willingness of a designer to bring in a newcomer (someone who was not previously engaged in the design effort) to the design team and overall design collaboration. Newcomers bring in new perspectives and different insights about potential new design approaches; however, the addition of new agents can also destabilize a team. Newcomers in the inappropriate quantity can lead to reduced final fitness values for the overall design process or longer times to market. This degradation of performance can arise, for example, from a lack of an appropriate technical background and expertise for the design problem at hand. Finding the right balance of newcomers in a design team mirrors the struggle of exploration (roughly a focus on fitness) versus exploitation (roughly a focus on search times) in general as newcomers contribute to the exploratory potential for a design activity. The potential of a newcomer to bring new insights depends on a variety of additional factors. Including the diversity of a newcomer where diversity between designers translates into the distances between designers on the design landscape. This measure conceptually represents the differences in the backgrounds and specialties among the designers.

ii. the propensity to repeat a collaboration,

   1. This parameter describes how likely a designer is to work with someone whom they are familiar with through their previous collaborations. Having groups who frequently interact with the same design participants can lead to highly cohesive work units with limited diversity; these interactions promote groupthink and at times contributes to the inability of a design team to find sufficiently fit design solutions. As in the case of the parameter that

governs newcomers, finding an appropriate balance depends on several factors. For example, for highly complex designs, having highly cohesive teams can quickly lead to design concepts but frequently these designs fail to meet value expectations or deliver the appropriate value to the user. Conversely, for designs that lack complexity, cohesiveness can lead to design that delivers value while also doing so in the least amount of time.

iii. the team-size,

    1. The number of agents contributing to a team determines how many resources a design effort can pull in at any given time. In the C^2D model, the team-size remains constant throughout the simulation. Having a larger design team leads to more design collaborations. As a result, a larger team allows the DAU and design-team to explore more of the design landscape. However, for larger teams the resulting negotiation between the designers (i.e. the resolution and consensus activities) in the DAU can result in greatly protracted periods of design, which limits its ability to respond quickly to getting products to market. As in the previous cases, the complexity of the design tasks also have important implications with regard to team-size. For highly complex tasks, smaller tactical teams (roughly four designers) will outperform larger groups. However, for less complex design tasks team-sizes tend to increase.

iv. the maximum allowable downtime for an agent, and in C^2D,

    1. The individual members of the DAU collaboration (i.e. a previous team-member) will only remain accessible to future teams for a given period before being otherwise engaged in new activities or losing interest. This maximum allowable downtime has important implications for an organization who relies on people in discreet increments and corresponds to the ability of a design enterprise to retain its talent and staff.

v. the maximum allowable diversity for a new newcomer

1. This maximum allowable diversity for a newcomer represents the degree of willingness a newcomer has for diverse perspectives when forming a team. This difference manifests itself in the model as a measure of the allowable distance from a designer that a newcomer can originate from on the landscape. The C^2D model goes beyond the initial concept of diversity from Guimerà et al. (2005) to include this explicit incorporation of diversity. This diversity differs in the sense that it provides the ability of a design effort to jump from one design concept on the landscape to another, potentially improved, design concept.

What this framework allows for is the ongoing generation of potentially unique design management strategies for mitigating the inherent complexity of the design tasks necessary for the development of an engineered system. For example, a manager for a design effort may explore strategies, using many of the parameters discussed above, to achieve improved design fitness or shorten the length of time required for a given design. These strategies could also include mimicking mechanisms from evolutionary mechanics, such as increasing the selection pressures on a collaboration. In nature, this occurs from pressures on a biological entity, such as rapid changes to the environment. These changes can lead to a shift or intensification of selection pressures on the survivability of a biological entity. In the DAU, a management system similarly may decide to limit their willingness to support design solutions that do not meet expectations for fitness. Similarly, the individual responsible for a design effort can examine if they should focus on bringing in newcomers for exploration or focus on exploitation using existing DAU members. This individual would frame their examination to consider the given the complexity of the design and their management objectives. Moreover, this platform allows for the discovery of unanticipated, potentially emergent, behaviors resulting from the interaction of mechanisms. In the C^2D model, these mechanisms include the rules and strategies employed by the design agents, their interactions, and their overall interactions with the environment. In effect, this model enables the discovery of beneficial patterns associated with design behaviors, specifically in terms of the capability of design agents to investigate design landscapes under varying degrees of ruggedness (i.e. levels of design complexity). Such simulations also have potential value in developing new approaches for managing the ongoing design planning activities, especially with regard to the allocation of resources and staffing.

For example, take the instance of a large aerospace engineering company, XYZ, who is endeavoring to make the first suborbital commercial jet liner a reality. Such an effort will require the coordination of a vast number of engineers across multiple disciplines (e.g., thermal, electrical, propulsion, computer programming, controls, aerodynamics, technical management, systems engineering). Given a candidate draft Design Structure Matrix (a mapping between requirements and design parameters) from initial conceptual design activities, the proposed C^2D framework allows the DAU management system to explore fundamental questions about how it wants to structure and engage its resources at each given design iteration. For example, does it want to encourage highly diverse large concurrent cross-functional team structures or would it benefit from smaller homogenous and highly cohesive teams. This approach allows the XYZ management system to ask several similar questions:

- How does the complexity of a design task relate to the performance of a design-team? How does it differ for small teams versus large teams?
- How does the complexity of the design relate to the likelihood of gaining improvements to fitness under various team configurations?
- What strategies will allow me to meet management objectives given the ruggedness of the design landscape?

The power of this framework is that it describes and captures the potential differences between different design approaches and their likelihood of success. Consider that XYZ is also a well-established company who is working in a niche but relatively stable market, which corresponds to working on a particular peak on a relatively static design landscape. The company may out of habit try to focus on taking advantage of its previous experiences. Although these experiences were valuable in allowing the company to find the peak from which it is currently operates, it may no longer be relevant in the face of the new design requirements. In the case of a highly complex design task like developing a suborbital commercial flight capability, the XYZ design organization will likely need to reexamine its position and understanding of the design landscape. The requirement for new propulsion systems and differences in environmental conditions, as well as differences in policy considerations, will likely dislodge XYZ from an exploitation and differentiation approach of design (one where it explores only its local neighborhood on the design landscape) to an exploration-based approach. Such a framework can allow XYZ to improve it understanding of the design environment and ask questions about how to best match to its new design environment. For example, it may provide value to XYZ by allowing it to judge how frequently the organization should hire outside experts and subject matter experts (i.e. how likely it should be to incorporate a newcomer) relative to its previous mode of operations. It also allows XYZ to consider how similar or diverse of a background they should consider in its hiring practices (i.e. the maximum allowable diversity).

Insights from the C^2D approach extend beyond XYZ to any design management system, allowing them to understand and explain why strategies are found and successful in particular design environments and what strategic processes (types of leadership, resource allocations, and particular parameterizations) best match to that environment. In general, the framework reveals that early in the design process a design management system should incentivize and reward a healthy degree of exploration, both in terms of the number of newcomers as well as their allowable diversity. However, later in the design process, conservatism often benefits the design process, especially if the complexity of the design tasks remain relatively low. This is because smaller and smoother design landscapes are easier for a design organization to understand and fully map, meaning that the organization has more assurance that it is terminating its search and design activities at a peak with a relatively high degree of fitness. These findings match nicely with many of the archetypal strategies discussed from the literature in an easily understood framework and visual representation (Mintzberg 1988, 1987; Miller 1987; Khandwalla's 1976). However, the applicability of these findings and generalizations remains dependent on the specific objectives for each individual design organization.

The framework highlights how design complexity, however, can also provide a design management system and its competitors multiple opportunities for differentiation. In this sense, design organizations that explore their local neighborhood remain focused on quality differences (e.g., addition of new features) to an existing product design. This attempt at product quality differentiation is suited to certain formulations for the design team, such as a limited degree of allowable diversity. Conversely, organizations committed to design differentiation that remain committed to high degrees of exploration (i.e. research and development engineering activities) may require a large degree of flexibility when it comes to the allowable diversity of newcomers. This diversity among its collaboration allows it to identify completely new locations on the landscape. This overall metaphor of the design landscape also highlights the need to monitor changes carefully to any of the underlying design elements of the landscape, such as requirement (e.g., technical, policy) and or technological changes, as even minute changes can entirely change the viability of a design concept. Although this framework provides only an initial approach, it is the hope that this initial conceptual bridge to the domain of engineering design and engineering design management will enable future design managers to develop new strategies and insights that will enable them to achieve continued success.

1

Introduction

“Aeroplanes are not designed by science, but by art in spite of some pretence and humbug to the contrary. I do not mean to suggest that engineering can do without science, on the contrary, it stands on scientific foundations, but there is a big gap between scientific research and the engineering product which has to be bridged by the art of the engineer.”

- British Engineer to the Royal Aeronautical Society, 1922.

The increasingly complex challenges posed by post-modernity highlight the growing importance of engineering design, the central process in transforming needs into solutions through the creation of engineering artefacts. The difficulty designers and engineering managers now face when satisficing progressively difficult demands underscores a lack of theoretical understanding. This research explores approaches for design complexity and performance management. The research focuses in particular on discovering beneficial design-team formation characteristics for mitigating design complexity. This research provides a framework that enables the following:

- ***Analysis*** of the challenges facing engineering design, which includes the exploration of performance in the context of both team-dynamics and structural design complexity, *i.e.* the complexity arising from interdependencies between design elements;
- ***Control and testing*** of complex design influences through modelling, providing the opportunity to examine and shape the determinants of design performance. The research focuses on the parameters governing team-dynamics and modifications of the design approach, *i.e.* the functional structuring of the design problem; and,
- ***Development of strategies*** that both mitigate structural design complexity and improve the effectiveness of design-teams engaged in the search of a complex design space.

As demands for complex engineered systems mount, the design process increasingly seems muddied for many practitioners.[1] Market demands for additional product value, new functionality, and increased efficiency of engineered systems drive an ever-rising effort on the part of manufacturers for continuous product development and improvement. These efforts continue to push the boundaries of design and increasingly drive complexity into both the artefacts and the design process itself. As a result, the designer must now not only overcome the technical challenges fundamental to their practice, but they must also contend with the nature of the complex systems that they endeavor to create.[2] Foremost amongst the resulting difficulties for the designer includes understanding and contending with *emergent properties* in design, specifically the unexpected behaviors that stem from the interactions between their engineered systems and their operating environments. Traditional approaches toward design, such as functional decomposition, often neglect these interactions and fail to predict their resulting unintended behaviors. In other words, engineered complex systems represent more than the sum of their highly engineered component parts, making decomposition techniques incomplete. Understanding these systems, their behaviors, and their performance requires a wider perspective of design and the design-team as a *complex adaptive system*, a dynamic network of interacting decision-making units that adapt their thinking to a design problem. Although the wider disciplines of science and engineering provide a tapestry of scientific tools and some general guidance, the modern process of design more accurately represents a host of difficult issues not present in other engineering domains, such as human creativity, decision-making and synthesis, uncertainty, and soft requirements.

Contrary to the traditional engineering focus, the *socio*-dynamics of design, specifically the dynamics of teams, represent an essential element of the design process. This work focuses on exploring performance in this wider context of design; the research examines the role of functional structuring of a design and the drivers of team-dynamics in the design process, all through the lens of complex systems. One of the central obstacles in meeting design objectives is the lack of real-time measurement systems of design performance and value. Given the varied facets involved in design, most approaches towards measuring performance focus on precisely measuring and comparing the relative inputs and outputs of a design system. This simplifying approach leaves

[1] We define an engineered system as an artefact-user system comprising hardware, software, people, facilities, processes, and procedures used to achieve a common object and resulting from a design activity.
[2] We use *designer* synonymously throughout the work to denote design and development engineers.

the underlying connective tissue between the outputs and inputs of design essentially an opaque *black box*. This conventional approach towards design fails to capture the important underlying dynamics that drive both *design performance* and *emergent properties* in design. Figure 1.1 sketches the characteristic *black box* approach to evaluating the performance of a system.

Understanding the essential driving forces of performance in design necessitates a more complete understanding of the actual transformative process between design inputs and outputs. To achieve this more comprehensive perspective of design requires opening the black box of design to explore design as part of a larger complex design-artefact-user (DAU) system. The DAU system relies heavily on relatively unexplored, yet necessary, *socio-technical* factors in its transformative role of converting the conceptualization of a system into the creation of an engineered system or artefact. Central to this work is conceptually relating the DAU as a complex adaptive system to elucidation of design performance, specifically design value and design-team performance.

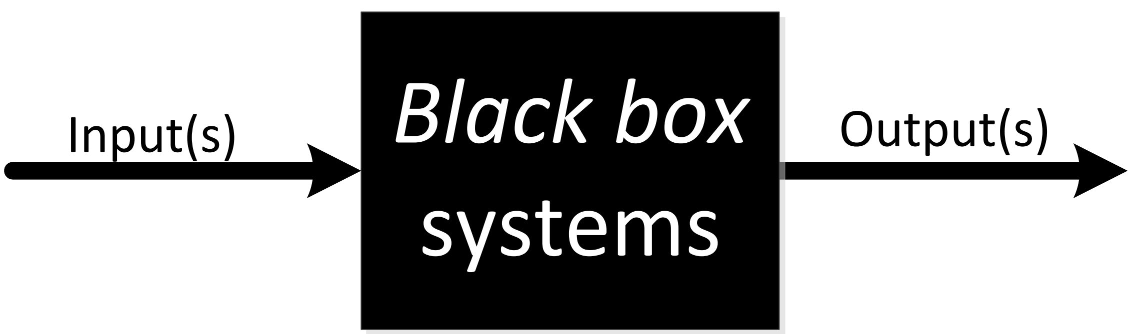

Figure 1.1 Black Box Approach for Performance Measurement. Traditional approaches for performance measurement compare the outputs and the inputs of a system to derive relative measures of efficiency. Performance measurement is a process that collects and analyzes information relating the activities, resource consumption, and production of an individual, group, or organization. As discussed in Chapter 2, the work examines the context of performance management in terms of productive efficiency and Data Envelopment Analysis (DEA) approaches. The successful management of these productions systems revolve around effective management processes for meeting input and output objectives. We use well-established concepts from natural systems and performance measurement to explore production in the specific context of engineering design efficiency and effectiveness. Specifically, the research provides a framework to explore performance in the specific context of the activities and interactions of the design-team, aspects of the engineering artefacts themselves, and the relationship between designers and users during the transformation of an abstract concept into a detailed engineering solution. These relationships from the basis of the designer-artefact-user (DAU) system discussed subsequently in Chapter 2. The research treats these DAU systems as both complex, *i.e.* comprising interdependencies, and adaptive, *i.e.* capable of changing and self-organizing to meet technical design challenges. Finally, the discussed *Complex Adaptive Performance Evaluation Method for Collaborative Design* (CAPEM-CD) or C^{2}D framework focuses on the collaborations that occur within this DAU.

1.1 Research Problem and Motivation

In part, the reason for the acceleration of complexity seen in engineering design derives from the very nature of engineering design, a process that inherently tends toward the creation of increasingly complex artefacts and refinements to improve efficiencies and effectiveness. In other words, design builds upon its creations in a self-edifying process of discovery and continual improvement (cf. Section 1.1.3). From its earliest successes, engineering design has pushed the boundaries of human knowledge in the creation of new technologies and artefacts. However, several recent engineering failures have left many current practitioners grappling with a central concern – has our approach toward design reached a fundamental limit in its continued progress? Moreover, can we as a design community no longer ensure the timeliness or even the safety of our creations? In the following sections, the research formalizes a statement of the problem based on this dilemma and highlight the motivation for our research.

As discussed in additional detail as part of the motivation and throughout the rest of this work, the complexity of engineering artefacts greatly influence not only the ability of designers to cope with the development of engineered systems, but it also may jeopardize the operational performance and safety of these systems. Some of the most egregious examples of engineering failures arise from the *emergence* of unanticipated system behaviors often resulting from system complexity; these failures continue to result in unfortunate casualties and calamitous impacts to the environment. The research defines this concept of *emergence* through the prism of complex adaptive systems discussed later in the section and after Holland (1999) as a pattern of behaviors and regularities that are true of the system as a whole, but for which the sum of components fail to capture (Holland 1999). The possibility of emergence remains in many systems engineering and safety approaches, as these approaches typically rely heavily on the decomposition and compartmentalization of a system to components and subsystems. In this construct design and safety considerations undergo a series of utility or reliability measures, respectively, based on a series of linear summations often without regard to the possible interactions that exists between the lower level components and subsystems. As discussed in more detail later in this chapter in Section 1.1.2.2, these behaviors represent real dangers to the operation and development of engineered systems as they become increasingly complex.

1.1.1 RESEARCH PROBLEM DEFINITION

Engineering design currently faces a rising trend of complexity. Successfully navigating the many uncertainties inherent to designing these complex engineered systems necessitates an improved understanding of the *socio-technical* factors driving design performance. By applying concepts from complex systems and performance measurement theory, this overall work provides a novel representation of design complexity and an agent-based approach that explores strategies to improve the way designers come together to collaboratively explore conceptual problem spaces with the goal of finding design solutions. The research uses an agent-based model to estimate the correlations between the way engineering design-teams form and their resulting performance under various regimes of complexity. Our goal is to use this information to inform and develop strategies that will enable design managers to better meet organizational design objectives.

By treating the design as a collaborative human ecosystem and as a *complex adaptive system*, this research explores the autonomous, goal-oriented, non-linear nature of human decision-making units engaged in the design process. By providing an inductive complexity science based approach towards design and design-team performance, this research establishes an alternative to the traditional deductive design science approaches for measuring design performance. The research represents the process of design as the exploration of a theoretical technology possibility space by design-teams. This work introduces the concept of a *design landscape* to represent a theoretical surface that bounds the theoretical space of all possible design outcomes. Allowing an agent-based collaboration of design agents to explore this landscape provides an overall instrument for understanding design performance. The developed platform discussed herein enables the ability to test and demonstrate beneficial *team-formation dynamics*, such as the use of parallel and highly diverse design-teams. The research intends for these insights to similarly inform the development of strategies that foster a supportive design and development environment that meets organizational objectives, *e.g.* maintain or improve time to market.

This research establishes a framework for representing and analyzing beneficial patterns of collaborative design behaviors. This developed framework will aid continued research efforts within the *System Performance Lab* (SPL) at Virginia Tech to create a rationale model linking the areas of performance measurement theory and engineering design science. This research also provides a platform to pursue research regarding the team dynamics and performance of collaborative productive systems for other domains outside of engineering design.

1.1.1.1 Theory of Design and Limitations

At the core of engineering is the goal of improving and creating systems, loosely defined as an integrated set of elements functioning together to achieve a pre-defined goal or function. In engineering design, these systems typically involve the creation of an artefact, product, or process. The study of engineering design science provides a general guide towards the creation of these systems. Prevailing academic approaches toward engineering design science utilize the same prism of scientific inquiry as its constituent engineering sciences: mechanics of materials, fluid mechanics, thermodynamics, dynamics, and etcetera. However, this comparison too often creates a false equivalency between *engineering design* and the *hard engineering sciences*. Design stands out as a qualitatively different entity, encompassing many difficult to quantitate aspects of social interactions, creativity, uncertainty, decision-making, and dynamic requirements. This work explores the differences between engineering science and engineering design approaches with the goal of developing generalizable connections between design and performance or value, as discussed in the research problem definition. This process of engineering design essentially represents the method through which individuals, often comprising a team, navigate a labyrinthine array of complex decision-making processes and changing environmental conditions. This process involves working across various distinct and relevant domains with varied but related activities; these domains and activities encompass eliciting needs (i.e. customers), describing functions (i.e. requirements), creating form (i.e. design parameters), and enabling process (i.e. manufacturability). Following from Kroes (2012), the Accreditation Board for Engineering and Technology (ABET) defines engineering design more broadly as the

> *"… process of devising a system, component, or process to meet desired needs. It is a decision-making process (often iterative), in which the basic science and mathematics and engineering sciences are applied to convert resources optimally to meet a stated objective. Among the fundamental elements of the design process are the establishment of objectives and criteria, synthesis, analysis, construction, testing and evaluation.*"

For purposes of this introduction, the research adopts a general definition of *design* from the literature as *the process of conception, invention, visualization, calculation, marshalling,* *refinement, and specification that determines the form of an engineering product* (French 1999). There remains a diversity of interpretations regarding *design*, pointing to the nature of the fundamental and ongoing research in the domain of design science. Given the broadness of these definitions, measures of performance for this process remain difficult to construct and relative to their application. For instance, the field of performance-engineering focuses on the ability of systems to meet a series of non-functional requirements that specify criteria used to judge the operation of a system, rather than specific behaviors of a resulting DAU system. These performance-engineering approaches generally focus on the properties of form (e.g., final artefact, output), the standards and processes used in its manufacturing, and the environment in which it must exist. These traditional measures of performance for design include, but are not limited to usability, maintainability, extensibility, scalability, reusability, security, and transportability. However, although these performance factors may provide some insight for users, managers, and manufacturers into the relative value of an individual design, they do not provide a measure of relative performance for the actual process of engineering design. Additionally, the disassociation of these *–ilities* from the requirements (i.e. functional domain) and customers (i.e. needs domain) limits their utility for informing the engineering design process when involved in the creation or innovation of a system.

Although the research restricts its definition of *design* to focus on *engineering design* as part of Chapter 2 (cf. Section 2.1), the work uses the term *design* throughout to represent an overall process, distinguishing *design* from the resulting manifested objects of design, which we refer to as the design or engineering artefact. The work further refines the definition of design provided to refer specifically to an ongoing and iterative process that occurs across multiple design phases (*i.e.* task clarification, concept generation, design embodiment, detailed design, verification and testing, and design communication) and across multiple domains of design (i.e. user, functional, physical, and process), as discussed further throughout the subsequent chapters.

Understanding the drivers of design performance across these phases of design posits significant benefit to both the economy and to the greater society, which both depend on the development of ever-increasing complex techno-social systems to meet their demands. These increasingly complex design requirements, often open-ended and ill structured in nature, suggest not only technical design challenges for the designer, but also, similarly, a new set of managerial and organizational challenges. Nevertheless, the perception of engineering design solely as a technical problem solving process and an issue of specification (i.e. the correct matching of function to form) remains pervasive, even among many practitioners. In stark contrast to these prevailing misperceptions, designers cannot simply apply routine mathematical formulas in a structured way to reach clearly optimal solutions (Dym 1994). The process of design, especially during its conceptual phase, commonly operates in a 'gray' zone, a complex space of multiple feasible solutions each with their own hard to quantify benefits and drawbacks. Exploring this zone, akin to a blending of the noösphere and technosphere, draws on the creativity and diversity of thought among designers. The inability of designers to apply clear utility-based optimizations hinders a design-team from converging efficiently around the selection of a final design concept, especially when the design-team lacks strong technical leadership or effective search strategies. These delays to the design process commonly result in both schedule delays and increased costs for manufacturers.

A growing body of work in engineering design, particularly regarding new product design, focuses on examining the sources of structural complexity in design and developing methods to structure the design problem *a priori*. Although this represents an important area in engineering design research, most of these research approaches lack consideration for the harder to quantify aspects of design, such as its dynamic collaborative and decision-making processes (Simon, Dantzig, Hogarth, Plott, Raiffa, Schelling, and Winter 1987; Diehl and Sterman 1995; Hollands and Wickens 1999). The actual engineering design of complex engineered systems, although highly technical, also encapsulates a highly interactive and social process that spans multiple, sometimes hundreds to thousands, engineers and stakeholders working on numerous interrelated components, ranging from thousands to millions of parts (Eppinger 2002). The interdependencies in a design often require frequent communication between the different responsible engineering designers of a system; these interdependencies between systems can commonly equate to innumerable coupled design decisions in the development of a typical complex system. In fact, research demonstrates that design engineers spend over half their time in various information behaviors, such as seeking information. The same research points out that, as a result of these activities, the skills of successful designers extend beyond their core competencies, drawing heavily on programmatic skills for the communication and coordination of tasks (Robinson, Sparrow, Clegg, and Birdi 2005; Robinson 2012). Common systems engineering approaches involve a largely top-down decomposition of design requirements, often ignoring coordination challenges posed by a design. Additionally, these decomposition approaches often fail to capture the interdependencies and unnecessary couplings within technical designs. Understanding performance in context of the engineering design process requires an examination from the perspective of design as a collaborative dynamic socio-technical DAU system occurring in state space. In other words, the relationship between the design, the artefact, and the user involves complex social and technical interactions that change over time.

Despite the essential nature of the inherent collaborative team dynamics in design, very few studies have linked design-team dynamics to design performance in a meaningful way. Given the findings from Guimerà, Uzzi, Spira, and Amaral (2005) that suggest the dynamics of team-formation in collaboration systems govern the overall performance of teams, the research focuses specifically on *team-formation dynamics* and their relationship to the ability of a design-team to search the technology or design possibility space. These team-formation dynamics include the likelihood of a collaboration to include newcomers, the tendency of a collaboration to repeat previous collaborations, and the size of design-teams. By augmenting these three simple parameters, it is possible to estimate, through modelling, the overall performance of a design-team engaged in the exploration of a hypothetical design possibility space that forms a *design landscape*. The *design landscape* provides relative value measures at different points along its surface and conceptually mirrors the *fitness landscape* heuristic used in complex natural systems (Gavrilets 2004).

This research intends to establish a conceptual and methodological bridge between newly emerging concepts from complexity science, established productive efficiency analysis and performance measurement theory, and the applied engineering design process. The overall purpose of this work focuses not only on ways to evaluate the relative fitness of a design or performance of a design process, but also on the application of a novel model-based framework for the generation of strategies that may improve a hypothetical design process. This research examines general methods for improving design in both the form of general strategies that incentivize beneficial collaborative team-formation dynamics and in the form of optimally structuring a design approach to minimize structural design complexity. The design approach, for purposes of this research, follows from the functional structuring of requirements in the design matrix. This structuring of requirements, as shown in Chapter 3, gives rise to the *design landscapes* discussed. The research further relates the optimum team-formation dynamics to the design approach, these insights include how the structuring of requirements in a design mitigates or induces real system complexity. This research focus supports the overarching objective of improving the design process (e.g. maintaining or decreasing time to market) by both elucidating the factors of design performance, particularly during the conceptual design phases, and by providing a new model-based platform for developing and testing strategies that minimize required design times.

The process of design represents the infrastructure for innovation and the mechanisms for intellectual production in the market place, yet the surrounding management systems and supporting design processes have seemingly failed to keep pace with the growing technical demands placed on the design-team. Design continues to grapple with questions of efficiency, efficacy, and proficiency in light of mounting complexity in the design of systems and their often-resulting stark failures (cf. Section 1.3.1). The importance of engineering design, despite a seemingly niche domain to many econometricians and performance measurement researchers, cannot be understated and motivates this discussion and research. The function of engineering design is almost indistinguishable from that of production for new systems; design is the process through which inputs transform themselves into outputs, *i.e.* the *black box* of many production systems (Buede 2000; Buede 2011). In the terms of the market, for the modern technology-based firm the effectiveness of a design effort can determine the ability of a firm to sustain its competiveness (e.g., generate product variety, close market gaps). Design further provides the mechanism through which most innovation occurs; the ability to continue these innovations represent an increasingly critical determinant in the generation of wealth on a global level (De Vol, Wong, Catapano, and Robitshek1999). However, how long can engineering and science continue to innovate and sustain its role as a key enabling mechanism in the economy? For many applications, it would seem the ability for designers to overcome the immense *socio-technical* challenges they now face maybe approaching a fundamental limit of designing in the presence of *complexity* and *complicatedness*. The research distinguishes between complexity and complicatedness in more detail throughout the work; however, in short we refer to complexity as the product of the interconnectedness of design elements and complicatedness as the product of the number of elements within a design.

Most managers, engineers, scientists, technologists, and analysts, as well as the public, have a familiarity with the symptoms of complexity, but apply the labeling of complexity itself to a problem in various ways. In the colloquial case for design, complexity represents an abstract notion to describe a cognitive barrier associated with increasing levels of aggregation, interdependencies, and nonlinear interactions. However, precise meanings of complex and complicated across the related fields of engineering design, acquisition, and engineering management often vary by individual. Table 1.1 demonstrates that distinctions within the terms, though subtle, do carry different attributes and connotations. The research defines *complexity* of an engineering design generally as the interconnectedness of design elements and, in so doing, distinguish it from *complicatedness*, which we define as a measure of decision-making difficulty solely from the size of a design (i.e. number of parts). This measure of complicatedness is simply a function of the number of design variables or size of a system or design effort. Several authors in the literature, dating to the initial investigations of complexity, from across academic domains (e.g., social science, organizational science, and engineering) suggest linking definitions of *complexity* to the size of a system (Terrien and Mills 1955; Anderson and Warkov 1961; Carneiro 1967; Salminen 2000; Cannon and St. John 2007; Regnell, Svensson, and Wnuk2008; Orfi 2011; Read 2012). However, the size of a system as measured by the number of nodes (e.g., people, requirements), functional touch points, or parts only provides a general correlation to *complexity*. This relationship does not directly represent the *complexity* of a system and more aligns to how we have defined *complicatedness*. We highlight this distinction in our general definition for design complexity, which involves the interconnectedness of design elements. Specifically the research defines design complexity as a measure of the interdependencies between design elements.

Table 1.1 Oxford English Comparison of Complicated and Complex

Complicated (adj.)	***Complex (adj.)***
1. Folded together (first usage circa 1660) 2. Tangled (first usage circa 1646) 3. Consisting of an intimate combination of parts or elements not easy to unravel or separate; involved, intricate, confused (first usage 1656) 4. Complex, compound (first usage circa 1667)	1. Consisting of or comprehending various, parts united or connected together; formed by combination of different elements; composite, compound. Said of things, ideas, etc. (first usage circa 1652) 2. Consisting of parts or elements not simply coordinated, but some of them involved in various degrees of subordination; complicated, involved, intricate; not easily analyzed or disentangled (first usage circa 1715)

Engineered systems, as in all systems, operate in the wider context of an environment, which we must take into consideration when considering definitions for complexity; the design and operation of these engineered systems requires locating and adapting to measures of regularity from the environment and regulating internal sources of complexity (Jost 2003). Both the shared common experience of engineers and the preponderance of the literature underscore the growing importance of understanding complexity and, in so doing, imply or categorically state the need for new systems for complexity management for the operations and design of engineered systems. Most everyone agrees complexity exists as a real phenomenon in today's world. Setting aside this agreement, the term and parlance of complexity more often represents an easy label that in itself provides a convenient scapegoat to dismiss project failures (Maurer 2007). This failure of understanding, with respect to engineering design, often results in a failure of the design to regulate and reduce sources of complexity. The result of these failures, to both cost and schedule, can limit the competitiveness of a design firm. Figure 1.2 demonstrates the dynamics of balancing and managing the design complexity to remain competitive.

The careless use of the lexicon commonly leaves treatment of complexity as palliative, regarding complexity as an unavoidable fate of design and their underlying dynamics as an almost uncontrollable (i.e. chaotic) factor. The common existing system engineering approach involves a largely top-down decomposition of design requirements, yet this decomposition often fails to recognize unnecessary complexity and coupling within technical designs. The future of successful design, especially given the multidisciplinary and collaborative aspects of design, requires the development of new techniques and new ways of thinking (e.g. bottom-up evolutionary) about design (Panchal 2009). These future design approaches and their definitions from contemporary literature increasingly align to foundational work from the study of complex systems and complexity science. Engineering design must increasingly pursue an understanding of the dynamics from complexity science to meet the inherent challenges of market requirements, *i.e.* designing at the point of maximal complexity known as the *edge of chaos*.[3]

[3] The edge of chaos refers to a maximal point of chaos between order and disorder (Holland 1990). The phrase dates originates from the mathematician Doyne Farmer who used it to describe the behaviors of cellular automaton as they underwent phase transition resulting from variations to an experimental variable. Kauffman (1999) similarly uses this term to describe the point of maximal rate of evolution (i.e. the rate of highest adaption).

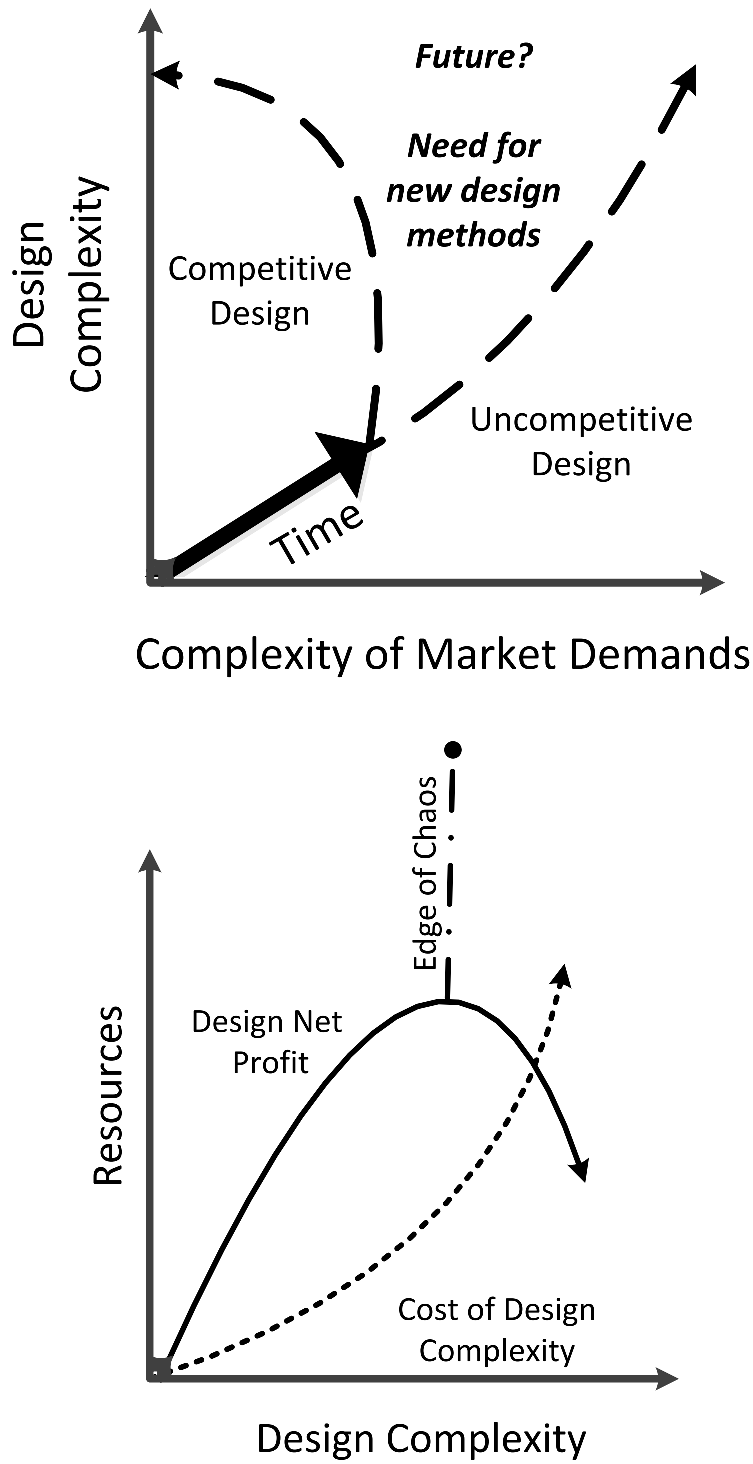

Figure 1.2 Market Factor Overview Incorporating Drivers of Complexity in Engineering Design. This figure provides an overview of the market factors and drivers of complexity in engineering design. This includes capturing how the inherent complexities in modern market demands (e.g. continued efficiencies, and multiple interdependencies) drive design complexity management systems to their limits (top), and how designing at the edge of chaos remains a pivotal challenge for the design of complex engineered system (bottom). Additional descriptions for the edge of chaos provided in the Appendix (cf. Appendix A)

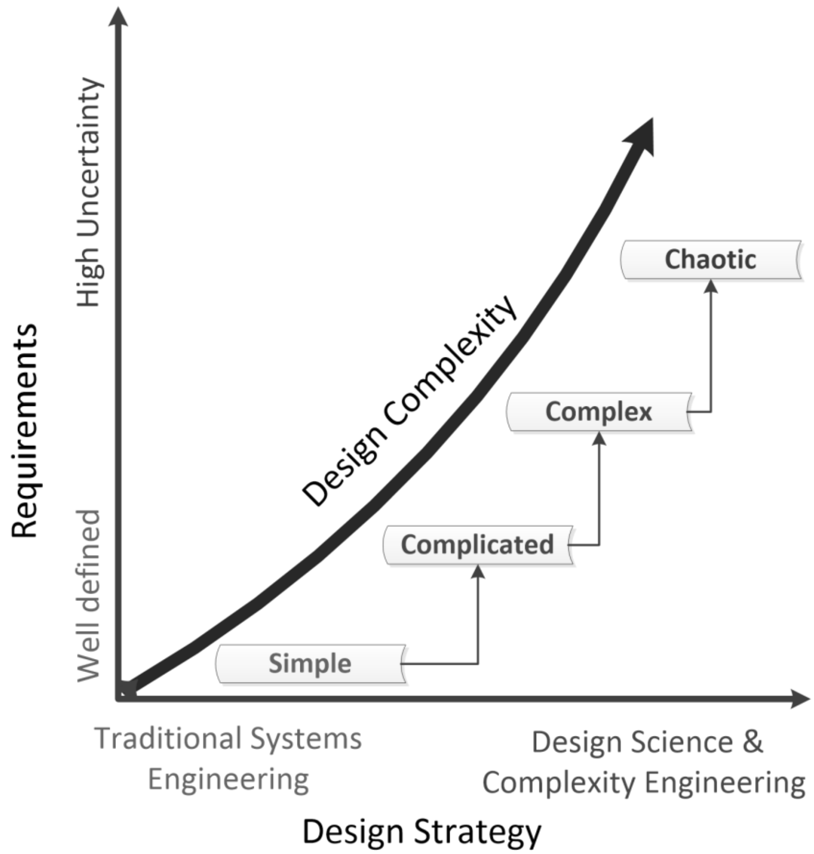

Figure 1.3 Typical View of the Continuum of Complexity in Engineering

Chen, Nagl, and Clark (2009) similarly find and state that there is a current lack of "much-needed" dialogue between complexity science and complex systems design and engineering communities. Within this effort, we focus use concepts for natural systems (such as complex adaptive systems) to the design of *complex engineered systems* where our goal is to not only identify and reduce system complexity and its unintended system behaviors where possible, but also to enable designers to overcome complexity where it persists. Specifically, the strategies developed should provide a robust set of behaviors for preventing unintended system behaviors from compromising the resilience and safety of engineered system. The research defines resilience as the ability of a system to operate through and recover, without degradation, its performance. We more broadly apply an understanding of *complexity* in design to the entire DAU system, a *complex adaptive* and *multi-scale system*.[4] These DAU systems contain various levels of abstraction with a high degree

[4] A multi-scale system is a system that exhibits important features at multiple scales, including both spatial and temporal scales (Wernz and Deshmukh 2010). The design process is an inherently multi-scale decision-making process; decision-making in design remains highly coupled through temporal, spatial, and organizational scales. This

of information heterogeneity, multiple sources of uncertainty, and they include multidisciplinary teams with sometimes competing objectives. In this context, a complex design often results when there is a strong coupling or path-dependency to previous design decisions, when design choices vary with time, when system behavior and their relationships to outcomes remain uncertain, or when there is a high scale order (i.e. size of design relative to smallest design component).

Further, the literature regarding engineering complexity divides the concept of complexity further into several types, to include *time-independent* and *time-dependent* forms of complexity (Suh 1990). In this context from Suh (1990), the *time-independent* forms of complexity include both real (i.e. known and measurable uncertainty) and imaginary (i.e. unknown uncertainty) components of complexity. Similarly, the *time-dependent* forms of complexity include both *combinatorial complexity* (i.e. future decision depend on past decisions, leading to indefinitely increasing complexity) and *periodic complexity* (i.e. combinations in design limited to a deterministic set, previous outcomes and decisions limited to a period). Many approaches, some discussed subsequently in Chapter 2, can help prevent *combinatorial complexity* in design through the functional structuring of the design requirements, *i.e.* the design approach. However, one of the most confounding elements in this reductionist approach stems from the growing interconnectedness and large degree of diverse interactions between multiple stakeholders and systems, especially from a system of systems context (Keating, Rogers, Unal, Dryer, Sousa-Poza, Safford, and Rabadi2003). Understanding and managing these interactions within the DAU system represents both a social and technical undertaking, *i.e.* a *socio-technical* challenge. The ability of the DAU to remain coordinated depends on the capability of designers to form and sustain effective teams. The success of these overall efforts depend on both the *socio*-elements of team dynamics as well as best practices for navigating the *techno*-aspects of design.

As discussed, most current approaches for engineering design, including design management, focus heavily on *techno-centric* approaches, despite the clear importance of these socio-technical influences and challenges (Trist 1981; Ropohl 1999; Baxter and Sommerville 2011). The principal cause for this techno-centrism stems from the ingrained behaviors of design managers who rely heavily on reductionist approaches acquired from engineering and scientific backgrounds, which

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coupling carries with it important implications for improving the exchange of information and enabling decision-making across the multiple agents that comprise a design-team.

treats questions of design as organizational and task-focused; as a result, design-teams generally approach design problems from a strictly technical and procedural orientation centered on the decomposition of systems (Baxter and Sommerville 2011).

Jorgensen (2008) traces the predominance of this approach in the history of design theory to a push originating in the Second World War era that focused on developing scientifically based engineering methodologies. Moving into the 1950s, engineering design, especially within the mechanical domain, maintained a heavily analytical focus, which concentrated mainly on the optimization of the individual elements and mechanisms forming the parts of the final artefacts in question. This techno-centric approach continues to permeate the design of technical systems; its influence remains especially evident in the guidelines and rules for embodiment design (Leyer 1973; Niemann 1975), and the design methods for product development (Roth 1982; Altshuler 1985; Koller 1985; Andresean and Hein 1987; Hubka and Eder 1988; Cross 1989; Pugh 1990; Ehrlenspiel 1995; Pahl and Beitz 1996). This approach has also shaped many of the various tools used in design, including tools for modelling, such as Computer Aided Design tools (Spur and Krause 1984), and tools for information and product-data management (Meerkamm 1996). These *techno*-centric approaches and tools often ignore the critical socio-dynamic factors inherent to the team based nature of design, and in so doing, they limit the ability of engineering design to handle contemporary complex interdisciplinary and technical challenges, such as emergent design properties. Most approaches toward design remain oversimplifications that characterize design as an array of routine decision-making processes and resource allocation optimizations (Bower 1970; Noda and Bower 1996; Simon 1969). These characterizations of design fail to capture the essential complexities and influences associated with managing a design-team, such as incentivizing the right collaborations at the right time.

Design sits at a crossroads; without the development of new approaches to manage design, the future of engineering design faces a strengthening vicious cycle that limits innovation. As organizations attempt to offset costly overages from failed designs, many organizations must decide to sacrifice future innovations for near-term gain, resulting in an appreciable disruption to the balance between exploitation of inventions, which, in the long-term, negatively affects the ability of the firm to create and develop new technology. Increasingly this trend limits the traditional engineering domains role in design to incremental development efforts and to the maintenance of existing production lines. Luckily, there are signs of recognition regarding the failures of these traditional approaches (Jorgensen 2008; Baxter and Sommerville 2011). Because of the continued difficulties traditional engineering design approaches face, Jorgensen (2008) points out the influence of traditional engineering domains continues to wane in the execution of major innovative efforts that were, until very recently, their former forte. In lieu of these traditional engineering approaches, major innovative efforts increasingly draw from diverse teams across multiple disciplines; for major innovations, these diverse backgrounds often range a wide spectrum, to include anthropologists, market analysts, psychologists, industrial designers, and other uniquely qualified individuals with experiences relevant to radical innovations. In the conventional systems engineering approach, a recursive decomposition of the design into subparts occurs. These subparts subsequently then successively undergo integration into larger and more complex systems. However, this design approach continues to show alarming failures, costing billions of dollars (Bar-Yam 2000; Bar-Yam 2003; Bar-Yam 2004; Braha and Bar-Yam 2004; Collopy 2009). The design of these complex systems must draw on new supporting organizational constructs that provide a more robust supporting environment.

1.1.1.2 Causal Relationships Driving the Problem Definition

Questions and concerns about complexity continue to circulate throughout research communities, engineering firms, and management circles alike (Clarence 2012). The importance of complexity in design stands out as an important area of conversation at all levels of the engineering firm, especially among those involved with new product development and complex engineered-systems. This growing recognition stems from an increasing awareness of the mounting interdependencies facing the frontlines of the modern organization, whether an engineering design firm or a financial services company. Costly overruns, schedule slippages, and unanticipated operational failure modes provide the realization of once previously held anecdotes from the front lines of design about the challenges and dangers posed by complexity within engineered systems (Tatikonda and Rosenthal 2000). Understanding the systemic motivators of complexity with regard to design requires a firm grasp of the causal linkages between the dominating market forces and technology aspects in design. The motivating pressures responsible for this rise in complexity have an almost universal origin. Ultimately, the driving motivation toward rising complexity may actually stem from the need to remain competitive. Figure 1.4 describes the dynamics that drive complexity in design using a casual loop diagram.

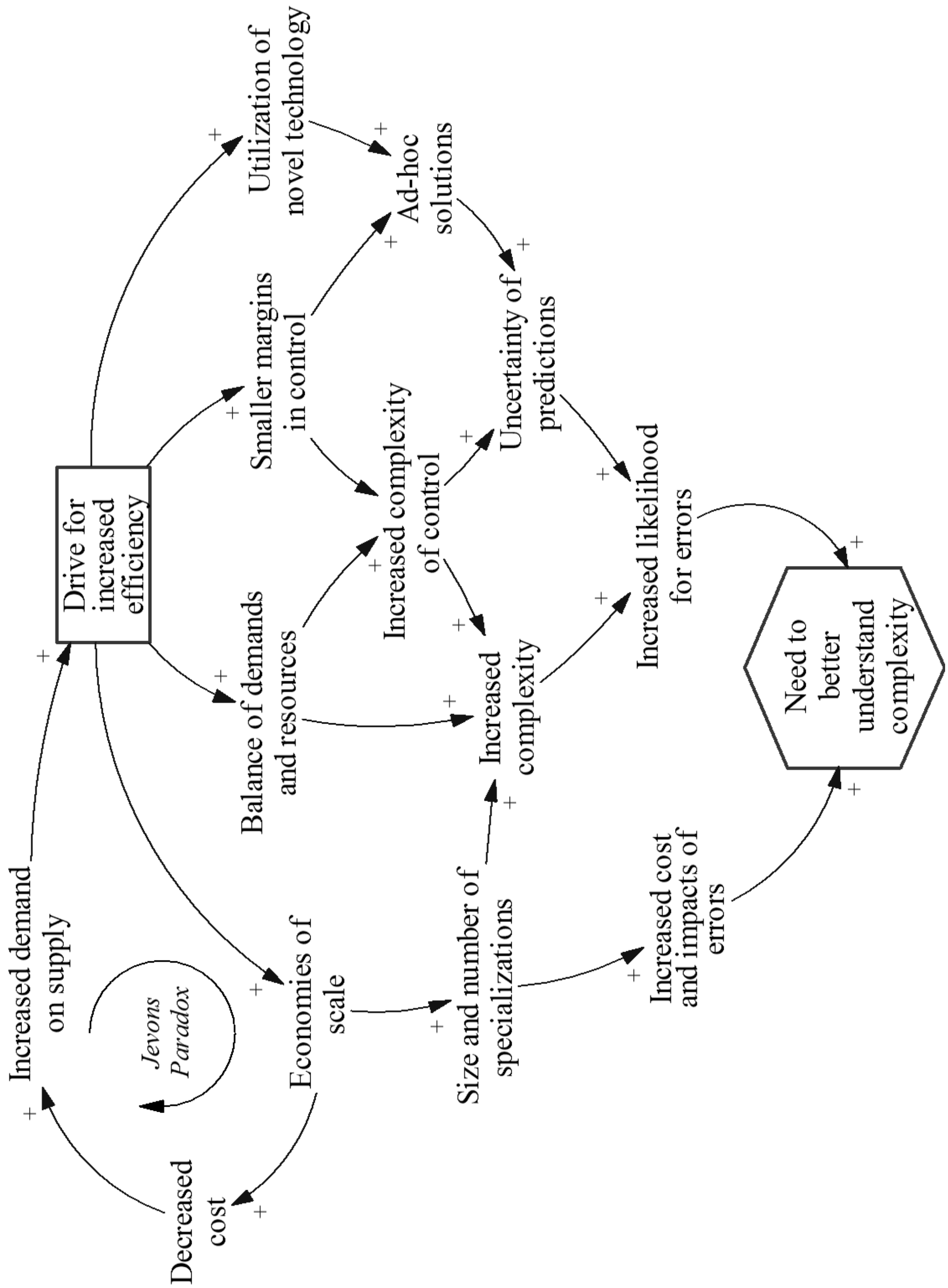


Figure 1.4 Drive for Efficiency Leading to Increased System Uncertainty and Complexity

In biology, this competitiveness and need to sustain fitness, *i.e.* fecundity or capability to reproduce, provides a central force behind a trend of increasingly complex adaptations. Analogously, the same pressures that allow a species to survive and grow within the context of the enterprise translate into a pressure for profitability and competitiveness in the modern marketplace. As organizations grow and enter new markets they expand their product lines and seek new market positions. It is in this vein that a driving system dynamic behind the increased product complexity arises from the market, *i.e.* each design of an engineered system continually attempts to improve (i.e. optimize) their relative efficiencies and market-share. This drive for performance, at a very high level of abstraction, results in increasing varieties and couplings, leaving a byproduct of complexity (Wahlstrom 1992). These motivators for greater relative efficiencies lead generally to an increasing rate of adoption of new technologies, an increased number and size of specializations, and an increased competition for resources. In design, the drive for shortened development cycles (i.e. shortened time to market) and lowered costs similarly drive the use of new and increasingly novel technologies, continually compromising the configurations of existing technologies (Cohen, Eliasberg, and Ho 1996). Figure 1.4 above depicts these dynamics. [5]

One of the key drives for increased efficiency revolves around the process domain of design, *i.e.* the manufacturability and time to market. Time-based market strategies dominate most product development efforts; for example, every day late when introducing a new car to market meant a profit loss of over $2 million dollars per day, measured in 2012 dollars, during the late 1980s (Clark and Fujimoto 1989). It is within these seemingly enigmatic confines that the engineering designer must now operate while trying to maintain time to market and deliver value. Additional data further underscores the importance of time-based strategies in most engineering design efforts. For example, data from Cohen, Greenberg, Hart, and Howe (1989) demonstrates how delays over six months translated into a 33% loss in total profit for new product developments. This form of opportunity cost greatly overshadows general cost overruns; in the example a 50%

[5] These overall dynamics raise interesting parallels about the elasticity of demand for new product development efforts and parallels Jevons paradox from economics. Jevons paradox implies that as efficiency improves so too may the rate of consumption and, subsequently, its demand; the economic literature refers to this as the rebound effect. Despite the logical assessment that increased resource efficiency would lead to less aggregate demand as supply increases, Jevons paradox manifests as the elasticity of demand surrounding technological improvements. These concepts parallel those from complex systems, where attempts to extract efficiencies increase performance only to a limit, the edge of chaos. In this region of maximal complexity, a balance occurs between order and randomness. In the economic analogy, this edge of chaos represents maximal efficiency similarly between order and randomness.

cost overrun only resulted in a net 3.5% loss to total profitability compared to the 33% total loss to profit for not reaching the market when planned (Cohen et al. 1989). It is therefore, not surprising that time to market pressures dominate the drivers for efficiency across engineering design firms when developing new products.

1.1.1.3 Brief Introduction to Complexity and Complex Adaptive Systems

An essential element of the discussion centers on the complexity of engineering artefacts and the DAU as a complex adaptive system. Our usages of these terms follow generally from the work of Holland (1999) and remain covered in detail as part of the literature review in Chapter 2. However, for purposes of this discussion we provide a basic primer for the reader. Even the simplest of management systems exhibit what Holland (1999) refers to as "perpetual novelty," a level of complexity generated by a large number of interactions among even a small set of autonomous agents. Perpetual novelty gives rise to a level of complexity beyond direct human comprehension and it remains largely intractable by current methods of analysis. Holland cites the game of chess as example of this perpetual novelty, a game that has only 12 uniquely different game pieces and only 64 possible game spaces on the board. Holland demonstrates mathematically that despite the relatively small number of individual players and the relative simplicity of the board, the chance of any two games of chess having played out in exactly the same sequence, throughout all of human history, is essentially zero. Perpetual novelty assures that new patterns of play can emerge continuously, even today, after hundreds of years of playing chess. The computer program known as Deep Blue further illustrates this concept. Only recently have the combined disciplines of computer science, mathematics and systems engineering been able to match a champion chess player's ability to win regularly in this relatively "simple" game of chess (Hsu 2002). If the game of chess exhibits this level of perpetual novelty, one can only imagine how the complex nature of human organizations and endeavors, such as those surrounding the design of engineered systems. We posit to the reader that even relatively simple engineered systems and artefacts (e.g. the latest cell phone), when examined through the lens of the DAU exhibit the characteristics of perpetual novelty and benefit from the forms of inquiry proposed and performed in this research.

As alluded to earlier (cf. Section 1.1.1.1), we envision the complexity of technology as a function of the interdependencies that exists between its elements and with the environment. More particularly, the research examines complexity through the relationship between functional requirements and design parameters and these requirements to a design environment. With regard to the DAU, the literature general defines a complex adaptive system as any complex macroscopic collection of relatively similar and partially collected microstructures formed in order to adapt to a changing environment, thereby increasing its likelihood of survival (Dent 1999; Mitelton-Kelly 2003). The research views the DAU as a complex adaptive system, more simply defined as any system containing a large numbers of components, often called agents, which interact and adapt or learn (Holland 2006). The straightforward, intuitive representation of the DAU collaboration and its decision-makers as a complex adaptive system allows us to represent the goal seeking behaviors of designers (often with competing preferences) and understand their behaviors as they explore and continually adapt to complex problems. This work closely associates the DAU to the CAS paradigm, and explore adaptive strategies for the DAU to improve performance through the construct of a design landscape (a representation of design complexity).

1.1.2. Research Motivation

The increasing degree of interconnectedness within and between engineered systems leads the designer to the current and unenviable position of having to make informed design decisions in the face of increasing uncertainty, which in turn, results in more rigid system definitions with increasingly less resiliency over time. This mounting complexity has not only meant the acceleration of emergent characteristics and the constraining of resiliency, but it has also entailed the extension of the effectual range for these deleterious behaviors and their resulting disruptive events to propagate. For example, the reach of a "normal accident" in the course of a complex engineered system, like that of a nuclear reactor, has much larger ramifications than for simpler systems as its influences many more systems and subsystems through its greater number of interdependent relationships. We now examine some of the ramifications motivating this research.

1.1.2.1 Exhibitions of the Engineering Crisis

Unfortunately, the struggles with complexity in engineering design qualitatively seem to be accelerating and their consequences escalating. Even a quick search of engineering failures in the popular press provides an alarming account of this occurrence. Numerous popular examples highlight how design failures and inefficiencies can quickly translate into cost and schedule overruns, sometimes leading to the complete abandonment of a project. Table 1 highlights several well-cited programs scrapped due largely to insufficient management of technical complexity.

Table 1.2 Commonly Cited Examples of Scrapped Projects Due to Complexity

Organization	System & Description	Time Frame	Outcome	Cost (USD)	Ref.
California Transportation Department	CALTRANS system to automate and modernize the trucking permitting process	2001-2008	Scrapped	$10M	[1]
California Department of Motor Vehicles	Modernized state system to tie vehicle registration and drivers' license system databases together	1987-1994	Scrapped	$44M	[2], [3], [4]
United Airlines	Planned unified IT service to provide automated reservations, ticketing, flight scheduling, fuel delivery, kitchen and general administration	1968 – 1970s	Scrapped	$50M	[2], [6]
California Child Support Services	California Child Support Automation System serves over 1.6 million cases and more than 10% of the federal child support caseloads. The system purpose was to provide payment services for the state as well as a centralized database for case management	1991-1997	Scrapped, *later variant in 2008 cost ballooned to $1.5B*	$110M	[2], [5]
Hilton, Marriott, Budget, and American Airlines	IT system concept based on a partnership between major hotels and American airlines to produce a combined hotel and airline reservation system	1988-1992	Scrapped	$125M	[2], [7]
K-Mart	IT system meant to improve a supply chain and inventory system failed and resulted in the final causes toward the retailer's nationwide pullback of store locations	1998-2001	Scrapped	$195M	[14]
United States Air Force	Advanced Logistic System (ALS) attempted to provide an integrated system for supply chain management and logistics.	1968-1975	Scrapped	$250M	[2], [8]
Veterans Affairs	Computer upgrade project to manage patient records in Florida	2001-2004	Scrapped	$472M	[15]
United States Air Force	Expeditionary Combat Support System (ECSS) was the latest effort to modernize over 200 legacy logistics systems with commercial off the shelf software with the goal of providing an integrated logistics and supply chain management picture	2005-2012	Scrapped	$1B	[9], [10]
British Stock Exchange	TAURUS trading system intended to transfer the London Stock Exchange from paper communication to an automated system	1990-1993	Scrapped	$100-600M	[2], [11]
Internal Revenue System	Tax Systems Modernization projects sought to unify the internal tax software systems	1989-1999	Scrapped	$4B	[2], [12]
Federal Aviation Authority	Advanced Automation System (AAS) attempted a big-bang approach to overhaul the air traffic control system, to include new tools and communication equipment	1982-1994	Scrapped	$3-6B	[2], [13]

Table 1.2 Commonly Cited Examples of Scrapped Projects Due to Complexity (Continued)

National Aeronautics and Space Administration	Constellation was a proposed program to fulfill the Vision for Space Exploration announced by George Bush to ultimately realize manned missions to Mars	2004-2010	Scrapped	$13B	[16], [17]
United Kingdom National Health System	The National Program for IT (NPfIT) was a move to unify records and electronic care for patients throughout England, covering over 30,000 general practitioners and 300 hospitals.	2004-2011	Scrapped	~$19B	[18]

*[1] Hancock (2009); [2] Bar-Yam (2003); [3] Appleby and Wilder (1994); [4] King (1994); [5] California State Auditor (1998); [6] Pantages (1970); [7] Oz (1994); [8] Ward (1975); [9] McWilliams (2012); [10] Stross (2012); [11] Braha and Maimon (1998); [12] Stengel (1997), [13] Mozdzanoska and Hansman (2008); [14] CNN Tech (2002); [15] Edwards (2005); [16] Pelton (2010); [17] Committee on NASA Cost Growth (2010); and,[18] Simons (2011)

These examples shed light on the growing crisis in the process of engineering design; the 'complexity crisis' as popularized by Mariotti (2007) represents a growing phenomenon in design and product development worthy of rigorous continued research. Large-scale government projects, exemplified in the defense industry, stand out as examples of large complex technical systems plagued by an astonishing growth in complexity. The examination by Meier (2010) of the US Department of Defense (DOD) shows that development programs currently average cost overages of 40% compared to their initial estimates and similarly average schedule delays that exceed 22 months. Maddox, Collopy, and Farrington (2013) provides a similar statistic showing that DOD loses tally over $200 million per day on large weapon system projects. In many instances, the common refrain is that these development programs struggle with their size and technical complexity of their associated tasks. A total value that on average could fund the entirety of National Aeronautics and Space Administration (NASA), the Department of the Interior, the Department of Commerce, and Environmental Protection Agency combined. In an assessment of selected weapon programs, the GAO (2008) went so far as to call one of the programs, the Joint Strike Fighter program, so overly complex as to make the entire program not executable. Interestingly, the findings from Meier (2010) suggest that these failures stem not only from the inherent technical complexity of the tasks (or the explosion of part counts), but rather from more subtle *socio*- and *organizational*- dynamics. In particular, Meier (2010) points out the limitations of the DAU systems used in large Government acquisitions and design efforts, which include ineffective human resource policies, market wide factors (e.g. consolidations in the aerospace industry), and too many stakeholders involved in the design and acquisition of systems.

Clearly, the reasons for the current engineering crisis remain multifaceted. In many cases, design difficulties result not only because of *socio-technical* reasons, but also from poor decisions that lack the proper considerations for the operating environment of the system and the complete lifecycle of the engineered system (i.e. deployment, operation, sustainment, and disposal). Although these factors, as well as additional secondary factors may contribute to these negative trends (e.g. incentives to underbid cost and schedule) in the development of defense systems, it remains clear that complexity plays an inexorable role in the design of large engineered systems writ large, including those from both the public and commercial sectors (Lewis 2012). The rise of increasingly complicated machines and systems (e.g., spacecraft, airplanes, and submarines) corresponds to this increase in complexity, mainly through its shared correlation. More components, in short, usually corresponds to a design that requires more *information content* to meet its functional requirements, which in turn introduces more opportunities for interconnectedness or complexity. This higher *information content* (e.g., the more precision required) the higher the engineering difficultly and a lower the probability of success for a design. Concurrently these complicated systems increase the likelihood that the performance of one design element depends on the performance of another design element, *i.e.* interdependent design elements. Figure 1.5 shows the trend of increasingly complicated engineering design challenges in terms of an effective part count. As discussed, this approach provides an initial correlation to *complexity*, and more accurately provides, as previously defined, a look into the *complicatedness* of new system.

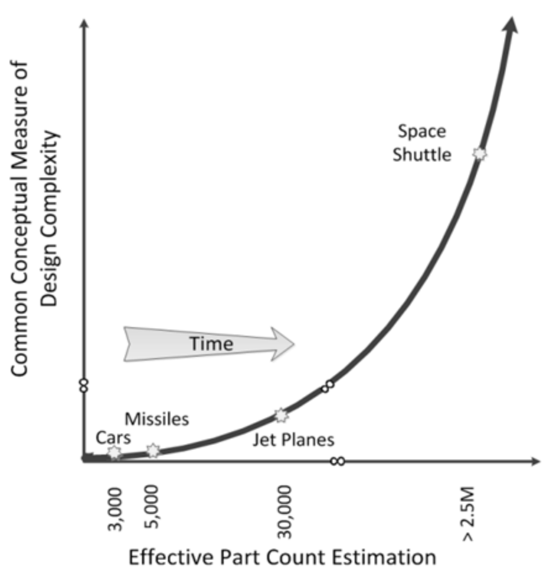


Figure 1.5 Explosion of Complicatedness in Design

For engineering design leads and managers, the ability to oversee and coordinate the design processes, including all of its decision making elements, depends primarily on its ability to address the structural complexity of the system (Tang and Salminen 2001). Many of the failures of the design process reflect limitations of the conventional systems engineering approach in both mitigating complexity and understanding the role of the designer in navigating the rugged resultant *design landscape*. The rising degree of project cancellations and costly overruns provide evidence of this failures and the need to reduce complexity in design and better understand how designers can improve their search of the *design landscape* for engineering solutions in its presence.

Good designers strive to create systems that meets functional requirements, while conforming to the axioms of sound engineering design, *i.e.* ensuring independence among requirements and minimizing required design information (Suh 1990). This axiomatic approach towards design (cf. Section 2.1.2) helps to maintain a maximally decoupled design; therefore, limiting the opportunity for *interdependencies*. Great designers not only have the ability to condense the necessary number of *design parameters*, the physical attributes of a design that satisfice the functional requirements, to the minimum amount necessary, but they also have deep technical expertise and the ability to fully coordinate their actions across the DAU system. This expertise provides them an intuitive understanding of the *design landscape*, and their ability to coordinate design decisions allows them to search the design possibility space more efficiently. However, in many of these highlighted cases the variety of design elements (e.g. distinct design decisions), even when given an optimally structured design approach, makes coordination nearly intangible and failures inevitable.

Examples of these coordination limitations most clearly arise from highly hierarchal and conventional large-scale complex design efforts. In hierarchical systems, such as those employed in most conventional engineering approaches, information bottlenecks through front line managers often impose coordination limitations on the design process. Many of these large-scale complex design examples do not necessarily fail, but result in astounding cost overruns; recent examples include the Joint Strike Fighter, the James Webb Space Telescope, and the Mars Science Lab. Table 1.3 highlights this sampling of recent complex systems. Figure 1.6 highlights all recent NASA mission systems. These systems are just examples, biased from the author's personal experiences working in the aerospace sector, which provide further illumination on the existence of an engineering crisis.

Table 1.3 Evidence of Escalating Cost Overages from Ongoing and Recent Projects

Organization	System & Description	Planned Cost (USD)	Final Cost, Then Year (USD)	Ref.
Mars Science Lab	The Mars Science Laboratory mission is part of the National Aeronautics and Space Administration (NASA) robotic Mars Exploration Program managed by the Jet Propulsion Laboratory (JPL) of California Institute of Technology. The project, announced in 2004, successfully landed the *Curiosity* rover on Mars in 2012. The total life cycle costs of the MSL project currently exceeds $2.5 billion.	$650M	$2.47B	[1], [2], [3], [4], [5], [6], [7]
Joint Strike Fighter	The JSF is a development and acquisition program to replace a wide range of obsolete fighter, strike, and ground aircraft for the United States and select allies with contracts awarded in 1996. The program resulted from the merger of the United States Department of Defense (DoD) Defense Advanced Research Projects Agency (DARPA) Common Affordable Lightweight Fighter project with the traditional DoD Joint Advanced Strike Technology projects. In 2009, reports from the Wall Street Journal, noted that Chinese computer spies compromised the program, calling into question the future efficacy of ongoing aircraft deliveries.	$1.9B	$4.2B	[8], [9], [10], [11], [12], [13]
James Webb Space Telescope	The James Webb Space Telescope is a next generation space observatory, planned as a successor for the Hubble Space Telescope and Spitzer Space Telescope, originating from a 1996 efforts with a planned launch of 2007. The telescope, optimized for observations in the infrared, includes a very precise and large (6.5 m) mirror assembly and complex design. Currently the planned launch extends well into 2018 because of design delays with the telescope components.	$500M	$8.835B	[14], [15]

*[1] Craddock (2007); [2] Atkinson (2008); [3] NASA/JPL (2008); [4] *The Space Review* (2010); [5] Brown (2009); [6] Leone (2011); [7] Leone (2014); [8] Mark (2000); [*9] Aerospace Daily* (1995); [10] Baker (2011); [11] Gorman (2009); [12] Reed (2010); [13] Shachtman (2010); [14] Berardelli (1997); and, [15] Leone (2012)

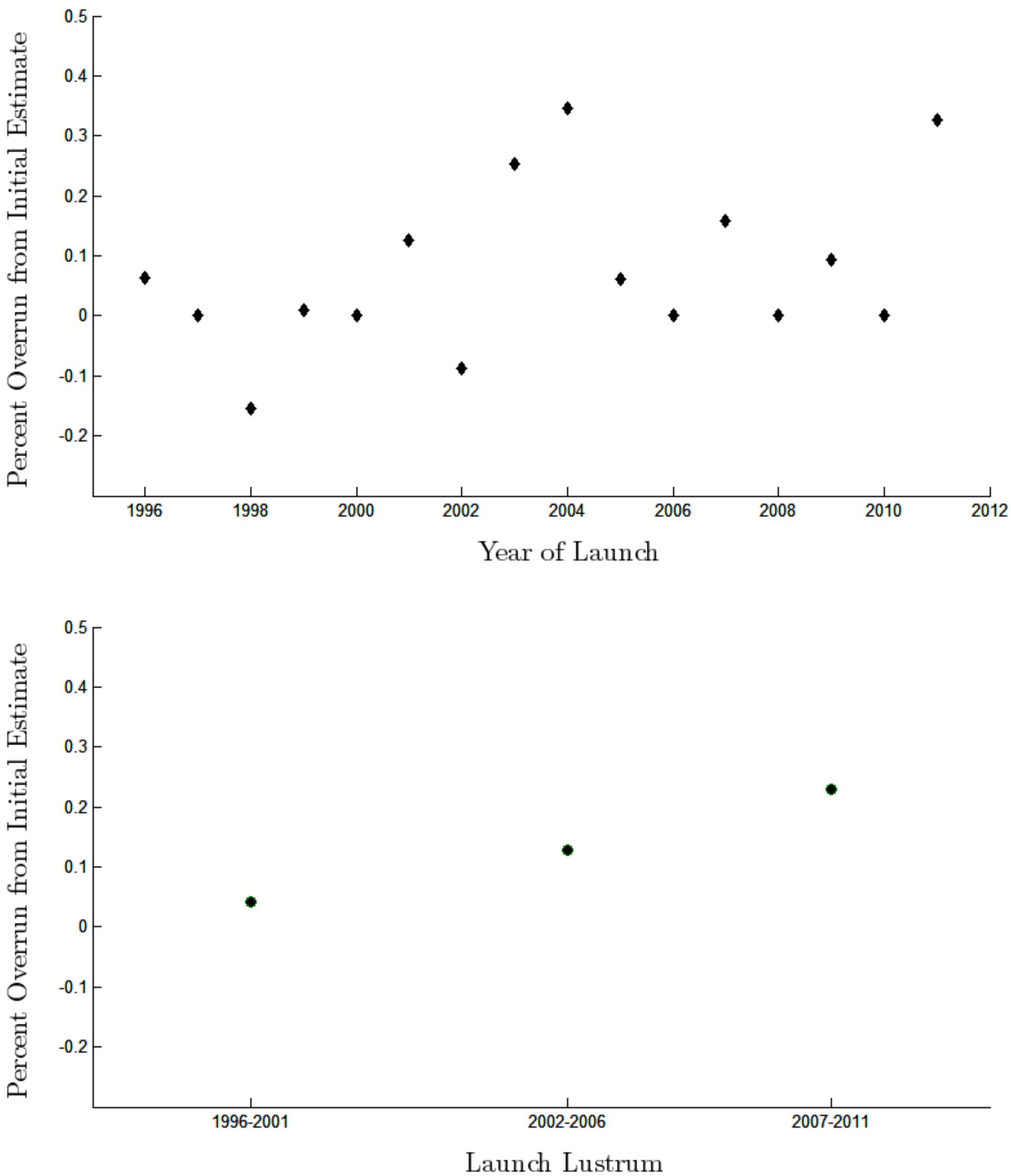


Figure 1.6 Trajectory of Mission Cost Overruns for NASA. The data for this figure includes data from the Mars Science Laboratory, from the years 1996 to 2012, and program data for other NASA projects by year (above) and by a cumulative look over a five year window (below) with data provided from GAO (2011, 2014) found in Appendix B.

The mounting difficulties for engineering design efforts, comes as no surprise to most technical practitioners and designers. Ongoing failures for large-scale complex projects underscore the inability of current design approaches to develop complex artefacts such as aircraft, submarines, space launch systems, and even automobiles (Collopy and Hollingsworth 2011). These cost overruns jeopardize the ability of many organizations to meet research goals and realize key strategic development objectives. This pernicious cycle of cost overruns spans not only the Government but includes technology development efforts writ large, including those within multiple private corporations. The challenges highlighted by these management and design failures oblige the examination of new paradigms for managing requirements and designing new systems, paradigms that aim to deliver value to the user as opposed to fully satisficing often competing requirements. Complexity not only degrades the efficacy of existing design processes but it also, as the research suggests, clearly relates to the mounting inefficiencies in the overall process of design (Orfi 2011). Unfortunately, the compelling need for improved management and performance systems for design extend well beyond project cost and schedule delays.

1.1.2.2 Danger of Emergent Behaviors

Examples of some of the most commonly referenced engineering disasters in the past include the Chernobyl nuclear disaster, the Three Mile Island accident, the Bhopal gas leak, the Hyatt Regency Hotel Walkway collapse, and the loss of both Space Shuttle Challenger and Columbia (Lawson 2005). These failures each resulted from an unfortunate combination of multiple factors, whereby the sum of individual defects or failures allowed for the system failure to occur, *i.e.* providing openings for errors to propagate through the system as typically described in the context of latent failure models for complex systems (Reason 1990). However, despite lessons learned and the continued refinement of operational protocols and procedures, similar and preventable engineering failures continue to amass. Most recently, examples of engineering failures have expanded beyond these standard examples to include, among others, the Gulf of Mexico Deepwater Horizon disaster, the Beyond Petroleum Texas City plant explosion, the Toyota hybrid vehicle acceleration failures, the Fukushima Daiichi nuclear disaster, the Orbital Science Antares rocket explosion, and the Virgin Galactic test flight crash. Part of the difficulty in preventing these disasters arises, in part, from the very processes employed to prevent them. The overt focus of error as a human or process problem, as opposed to recognizing and enabling the adaptability of systems to respond, often results in systems with limited controllability and minimum adaptability.

Each of the highlighted examples resulted from a set of unintended and emergent operating behaviors, arising from, in many cases, a combination of unforeseen fluctuations in the operating environment and conditions. As discussed, complexity in engineering design can lead to these emergent behaviors. The research defines an emergent behavior specifically as any unexpected response arising from the operation of an engineered system due to its interdependencies. Traditional systems engineering and safety analysis techniques focus on the decomposition of systems and the reliability of individual system components, providing at most an incomplete picture of system behavior. However, this represents at times a fool's errand in the instance of complex systems as perpetual novelty ensures that the interactions between system design components continuously gives rise to new emergent modalities and behaviors for the system. Highlighting again the need to create systems that can improve their adaptability to change, which in part motivates the research to use a complex adaptive systems framework in its exploration. Some of the most egregious examples of engineering failures originate from the emergence of unanticipated interactions between the design elements of the artefacts, the environment, and the users, *i.e.* these interactions often results in emergent operating behaviors. These failures continue to result in unfortunate casualties and even potentially calamitous impacts to the environment.

Complexity science often views general emergent properties as arising from the self-organization attributes and interactions between the environment and agents (Buchli and Santini 2005). Although self-organization in many ecological systems represents the natural order of events, this property when applied to design, especially when it comes to highly technical engineered systems, may lead to unforeseen outcomes and a real danger for system behavior. Future and ongoing research looks at ways to embed resiliency in engineered systems to overcome and even incentive positive forms of emergent behaviors, leading to virtuous dynamics for the performance of these engineered systems. The provided examples underscore the real dangers that can result from unintended and emergent system behaviors stemming from the complex and often-nonlinear interactions with previously unknown or unpredicted interdependencies. These events continue to provide a lens that sharpens public concerns with the management and design of these complex systems (Wahlstrom 1992). Aside from these highly visible disasters, numerous other examples from the design of complex aerospace systems (e.g. 1970s DC-10 failures, Columbia, Challenger, Skylab) similarly offer quintessential examples of the challenges arising from increased complexity during the design process; these examples demonstrate how early conceptual design failures often impact the proper function and operation of engineered systems (Sobieszczanksi-Sobieski and Haftka 1997). Moreover, each of these failed systems represent more than the failure of a gadget, they represent a larger socio-technical systems whose failures highlight the capacity of these socio-technical engineered systems to harm both the public and society.

Due to the rapid growth of system complexity in modern engineered systems, a growing set of possibilities for emergent and unexpected system behaviors exist. The need to understand the influences of complicatedness and complexities in design represents not only an obstacle to overcome, but stand out as an inexorable and fundamental characteristic of engineering in the 21st century (Meshkati 1991). Buchli and Santini (2005) highlight that self-organization can also provide very desirable properties with the appropriate incentives. Incentivizing casual mechanisms, *i.e.* creating an ideal design environment, for desired design attributes (e.g. robustness, resiliency, and adaptability) may actually help to improve the robustness and safety of highly complex engineered systems and artefacts; this possibility represents a cutting edge of research surrounding evolutionary design theory (Greene 1996). Embracing this challenge may usher in the increased adoption and improvement of these relatively new and novel methods for engineering design, such as evolutionary design. Methods for design require a new complex systems thinking perspective and are essential in meeting future design and development requirements. Supplanting the conventional '*systems' thinking* found in systems engineering with a *complex 'systems' thinking* perspective may prove essential in engineers and designers persevering over the wicked problems and *socio-technical* challenges confronting the twenty-first century and beyond.

1.2 Research Objectives & Approach

The overarching objective of this research is the synthesis of the multiple factors most influencing design performance into a parsimonious framework. These objectives include:[6]

- To complement current forms of design performance analysis;
- To establish a bridge linking the design process to complex adaptive systems thinking;

[6] We consider the proposed framework parsimonious as it provides a large explanatory power while limiting the number of predictor variables to a small core; in particular, the core functionality of the C^{2}D model depends on relatively few parameters for the team-formation dynamics and two-variables (N, S^*) for the *design landscape*.

- To augment the growing area of design complexity management with new tools rooted in a complex adaptive systems metaphor;
- To evaluate the relative importance of structural complexity in design-team performance;
- To evaluate the role team-formation dynamics has on overall design-team performance;
- To demonstrate the value of agent-based simulation in the analysis of design-team performance as a complex adaptive system;
- To demonstrate strategies that may improve the design approach and incentive beneficial patterns of behaviors within design-teams that improve search performance;
- To demonstrate the ability to generalize this research to a larger class of problems than is possible within the scope of this research; and,
- To identify appropriate topics for future research in this area

In particular, the research explores these objectives through the following thrusts:

- Modelling the technology possibility space by using the design and product matrix to form a design landscape;

- Modelling the ability of the design-team to find an overall feasible design solution when faced with an increasing degree of coupling (i.e. interdependencies) in the requirements space, *i.e.* design landscape; and,

- Modelling the role that variations to key design-team formation dynamics has on the time it takes a design-team to search the design landscape

As discussed, to accomplish these objectives the approach adopts a broader perspective of engineering design as a *socio-technical* process. For our purposes, the research build upon the concepts of the Complex Adaptive Productive Efficiency Model (CAPEM) by Dougherty, Ambler, Triantis (2014) to consider designers as individual agent-based decision maker. We build upon this existing effort to apply complex systems thinking to performance measurement by establishing an intuitive framework for describing complexity. Complexity manifests itself in the presented *Complex Adaptive Performance Evaluation Method for Collaborative Design* (CAPEM-CD) or, for short, the C^2D framework as the ruggedness (i.e. the variability in peaks and valleys) of a *design landscape*. The research links the team-formation dynamics central to this work to the design possibility space through this *design landscape*. The result provides a topological surface that relates the form-function relationship to fitness values. These fitness values provide a measure of performance, and remain synonymous to theoretical value-functions from value-driven design (Collopy and Hollingsworth 2011). Exploring this construct with agent-based design-teams allows us to examine factors that influence search performance characteristics; in particular, the research focuses on the role the structuring of the design matrix, *i.e.* the complexity of the design, has on the search characteristics and performance of these design-teams. This research discusses this complex systems approach and the design landscape in more detail in the subsequent chapters.

This approach provides a strong heuristic for both visualizing and interpreting the influence that key parameters of collaboration dynamics have on the search behaviors over a rugged landscape. Using this approach, the research explore what makes a design "good" and what makes a high performing team. Successful strategies and characteristics inherent to "good" designs surface as these agent-based design-teams explore the design landscape. This approach remains extensible to further exploration at the frontiers of design science, including the exploration of methods for harnessing design complexity effectively such as using simple incentive mechanisms that guide designer behavior toward organizational goals and objectives. The following work provides a piece of the puzzle to creating a platform for investigation and an initial inquiry into design as a collaborative *socio-technical* complex adaptive system. Moreover, by understanding how design-teams come together and behave while exploring a complex design landscape we develop insights and strategies for the improvement of design teams and their ability to come together.

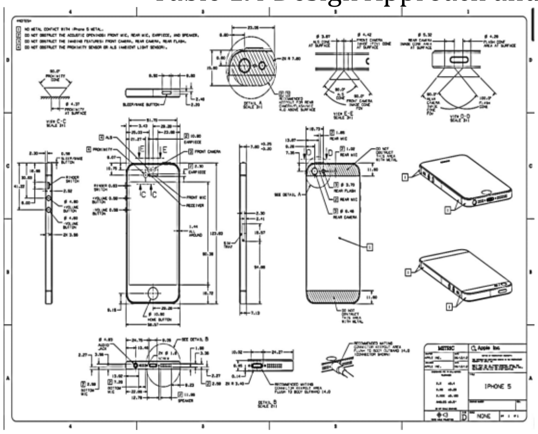
1.3 Clarifying Example

In order to clarify the key elements of the work, the research provides an example that covers each fundamental aspect of the work. The research expands on the theoretical approach and mechanics of these items in the coming chapters, particularly Chapter 3. Nevertheless, we use this example to allow the reader a glimpse of the "forest" to provide context. Let us consider a simplified examine of the design of a cell phone. The first step in our process is creating a design landscape to represent the underlying complexity or interconnectedness of a design. To do this we look at the relationships between the functional requirements and design parameters of a conceptual engineered system. Let us assume that the designers have received the following user need:

> *"I need a dependable cell phone, whose battery lasts for at least three days, and has an interactive display."*

Designers in coordination with the users have now worked to transform their understanding of this system into four basic functional requirements or FRs (i.e. provide software control, provide three day battery life, deliver 99.9% acceptable performance, and provide an interactive visual display) with four corresponding basic design parameters or DPs (i.e. Java software runtime v5, 3000 milliamp hour rechargeable battery, Chipset AMD JX-43, and a LCD display).

Table 1.4 Design Approach and Dependencies Given by the Design Matrix

	**DP_1 : Java Software Runtime**	$DP_{1.1}$: *Audio Visual Device*	$DP_{1.2}$: *Memory*	$DP_{1.3}$: *Wireless Link*	$DP_{1.4}$: *Keypad*	**DP_2 : 3000 milliamp hour**	$DP_{2.1}$: *Charging circuit*	$DP_{2.2}$: *Battery Montior*	$DP_{2.3}$: *Battery Compartment*	$DP_{2.4}$: *Provide Power*	***DP_3 : Chipset AMD JX-43***	***DP_4 : LCD Display***
FR_1 : Provide Software Control	O	-	-	-	-	O		-		-	O	O
$FR_{1.1}$: Communicate with User	o	-	-	-	-	o		-		-	o	o
$FR_{1.1.1}$ – *Provide State of Health*	-	X			X			X		X		X
$FR_{1.1.2}$ – *Enable Text/Phone*	-	X			X					X		X
$FR_{1.2}$ – *Store Programs*	-		X							X	X	
$FR_{1.3}$ – *Load Programs*	-		X	X						X		
$FR_{1.4}$ – *Accept User Inputs*	-				X					X		X
FR_2 : Provide Three Day Battery Life	O	-				O	-	-	-	-	O	O
$FR_{2.1}$ – *Charge Battery*						-	X	X		X		
$FR_{2.2}$ – *Communicate Charge Level*	-	X				-	X	X			X	X
$FR_{2.3}$ – *Allow User to Replace Battery*						-		X	X			
FR_3 : Provide 99.9% Availability	O	X		X		O				X	X	X
FR_4 : Interactive Visual Display	O	X	X			O			X	X		X

*Italics provide the lowest level of the design tree depicted and bolded items provide the highest level of the design branch or tree. The use of "X" represents a dependency between the lowest level implementations. The use of "O" represents the top-level complexity, *i.e.* with respect to the highest level of the design tree. Similarly, "-" marks contributing fields of interaction at the lower level to the top-level of a design tree or branch.

Table 1.4 above captures the requirements and possible satisficing design parameters into a conceptual design matrix. The research equates this design matrix to the design approach throughout the work. Although each of these functional requirements may undergo refinement and further specification, we use this example to provide a high-level illustrative depiction of the major elements of our research. From inspection of the design approach we can easily see that each of the four major functional requirements remain highly intertwined to one another through their shared design parameters. In fact, the design at its top-most and unreduced level has four functional design entities ($N = 4$) that each maximally couple to the other remaining three entities ($K = N - 1 = 3$). At this level of inspection, we cannot satisfice one requirement without simultaneously evaluating all functional requirements and their associated engineering design trades. As a result, solving the design parameters for the system of design equations independently becomes impossible and finding mutually satisficing solutions (i.e. a common range of values) extremely difficult. This gives rise to highly rugged design landscape, as discussed earlier.

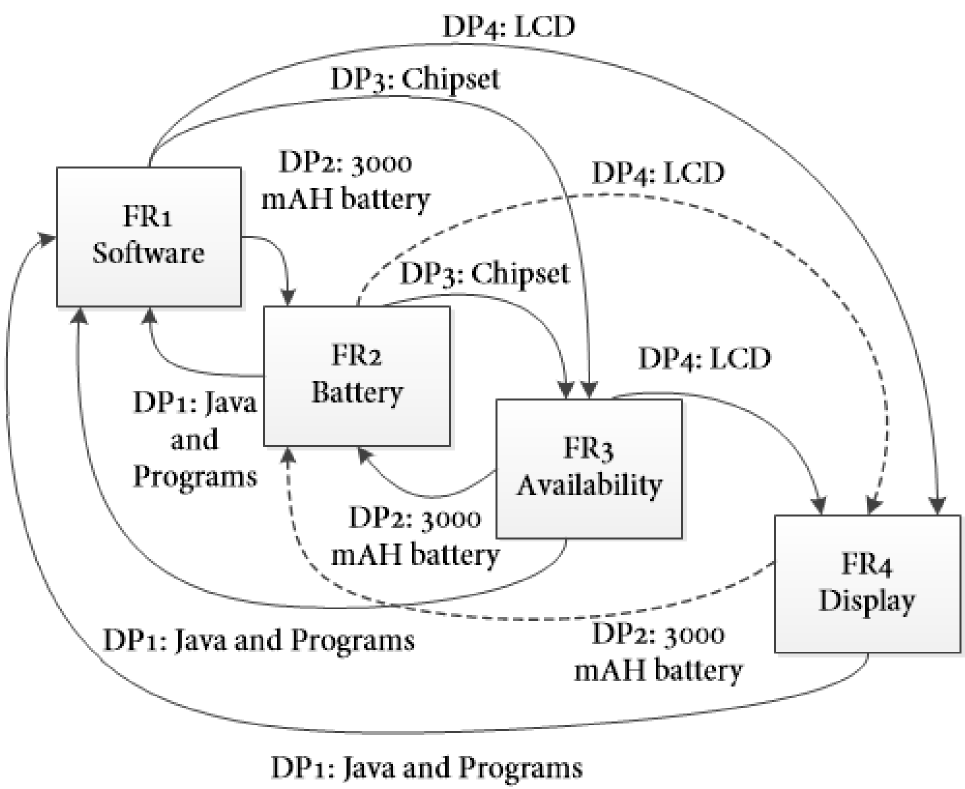


Figure 1.7 Design Approach Representation. This design includes four functional requirements each interacting with the three remaining functional requirements through shared design parameters.

Figure 1.8 demonstrates potential differences that the level of specification can have on the resulting complexity of the system under inspection; we show a maximally coupled design system (top) and the current design example at a more granular level of inspection (below). By examining the design approach at this granular level, we arrive at a greatly improved picture as seen in the figure. At this lower level of inspection, the system now has 10 functional elements and the design parameters include a much lower degree of coupling (bottom of figure).

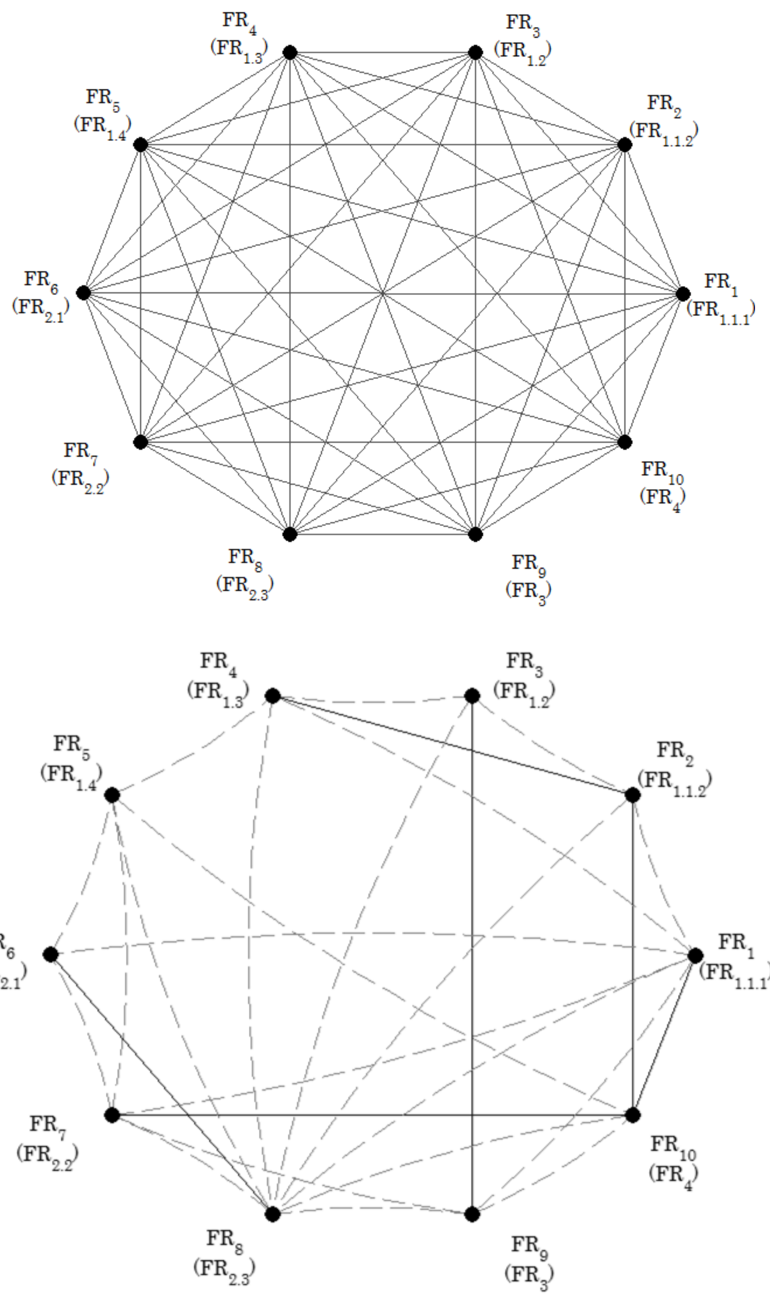
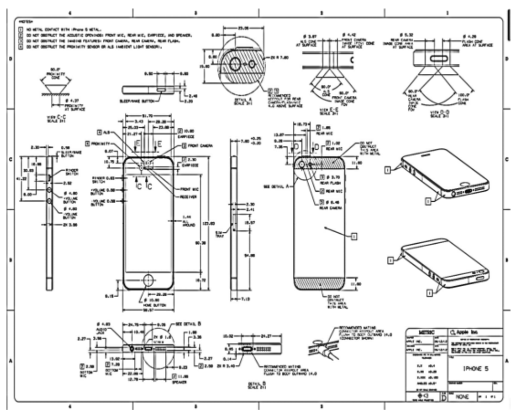


Figure 1.8 Directed Graph to Represent Design Adjacency Matrix (Directed Connections Dashed)

Although this improves the level of complexity, we can further decrease coupling by rearranging the design matrix using techniques from Axiomatic Design (Suh 1990). Table 1.5 demonstrates the new design matrix after we reduce the structural complexity as much as possible. This form of the design matrix is what we presume in the design approach throughout the remainder of the research unless otherwise specified. We can notice improvements to the interdependencies in the updated directed graph in Figure 1.9. Using a technique developed as part of this research (cf. Chapter 3), we can now estimate the relative complexity of this design approach using an NK approach based on the original Kauffman (1993) mathematical model. Here we similarly have $N = 10$ functional components, but an improved value of interconnectedness given by the variable K of 2.8, corresponding to a complexity score, proposed herein, of 31.1% given by the density of local optima on the design landscape, *i.e.* $K/(N-1)$.

Table 1.5 Design Approach and Dependencies Given by the Revised Design Matrix



	DP_1: *Audio Visual Device*	DP_2: *Memory*	DP_3: *Wireless Link*	DP_4: *Keypad*	DP_5: *Charging circuit*	DP_6: *Battery Montior*	DP_7: *Battery Compartment*	DP_8: *Provide Power*	DP_9 : *Chipset AMD JX-43*	DP_{10} : *LCD Display*
FR_1 - *Interactive Visual Display*	X	X					X	X		X
FR_2 - *Provide 99.9% Availability*	X		X					X	X	X
FR_3 – *Provide State of Health*	X			X		X		X		X
FR_4 – *Enable Text/Phone*	X			X				X		X
FR_5 – *Communicate Charge Level*	X				X	X			X	X
FR_6 – *Store Programs*		X						X	X	
FR_7 – *Load Programs*		X	X					X		
FR_8 – *Accept User Inputs*				X				X		X
FR_9 – *Charge Battery*					X	X		X		
FR_{10} – *Allow User to Replace Battery*						X	X			

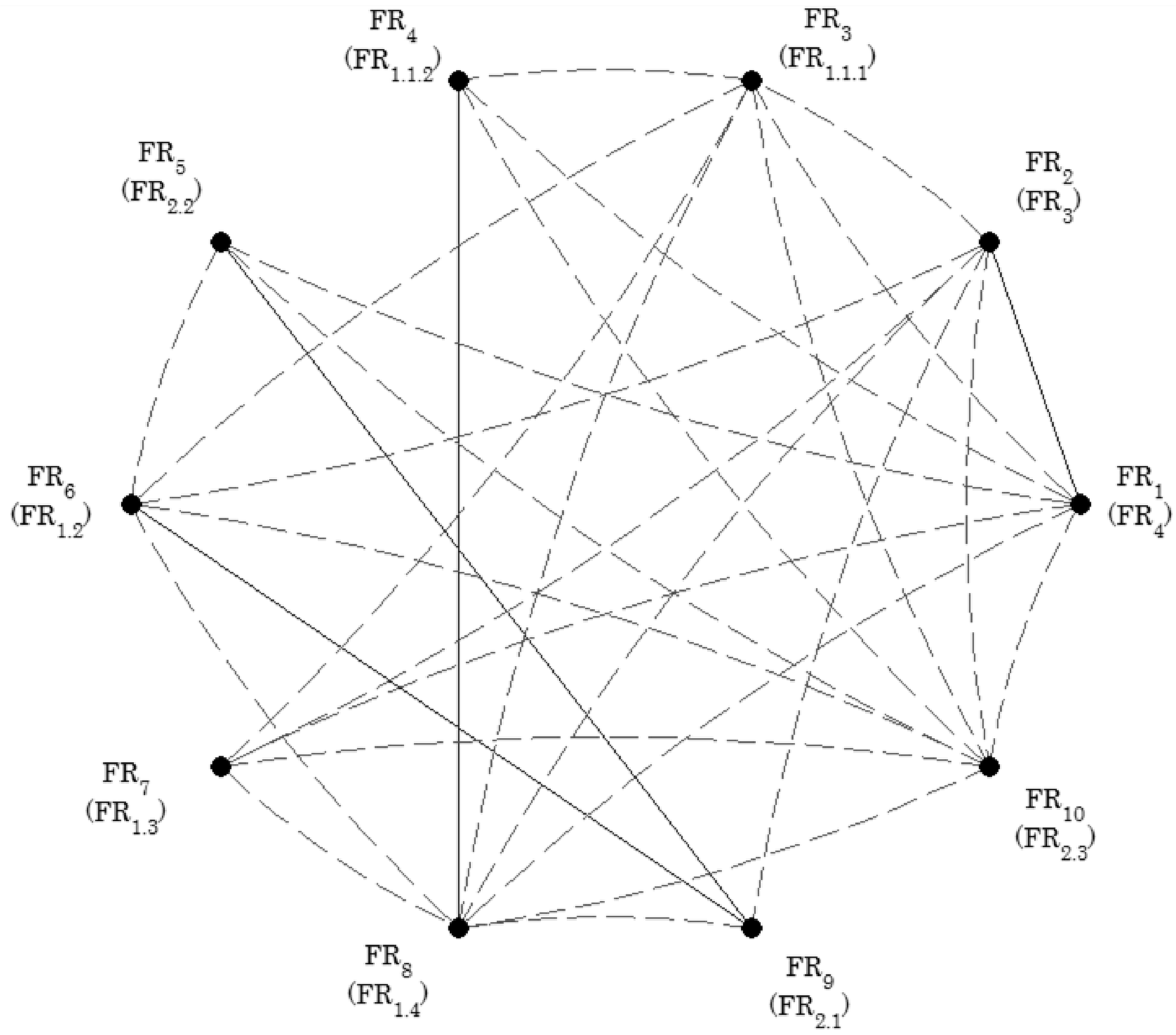


Figure 1.9 Directed Graph. This graph represents the new design approach, as before the undirected (or two-way) connections use solid lines and the directed (or one-way) connections use dashed lines.

So now that we have estimated the complexity of the design space, based on a series of relationships discussed in Chapter 3 (cf. Section 3.3.4), we can proceed to generate a representation of this complexity using a fitness landscape. This landscape provides us the representation of the underlying design approach.

1.3.2 DESIGN LANDSCAPES

As already introduced, we use a fitness landscape, which we call the design landscape, to provide a simple and meaningful representation of the underlying design matrix in our approach for evaluating and simulating complexity as it relates to the DAU. Although, left primarily for future discussion, we can generate these design landscapes based on the values of N and K derived earlier.

Figure 1.10 demonstrates the corresponding landscape for the example shown above ($N = 10$, $K = 2.8$). In this figure, the research provides the three-dimensional fitness landscape (top) where height corresponds to fitness (i.e. design performance) and the equivalent two-dimensional gradient fitness landscape where intensity corresponds to fitness (bottom). As seen, the landscape has multiple potential attractors (i.e. local optima), despite being a relatively smooth landscape.

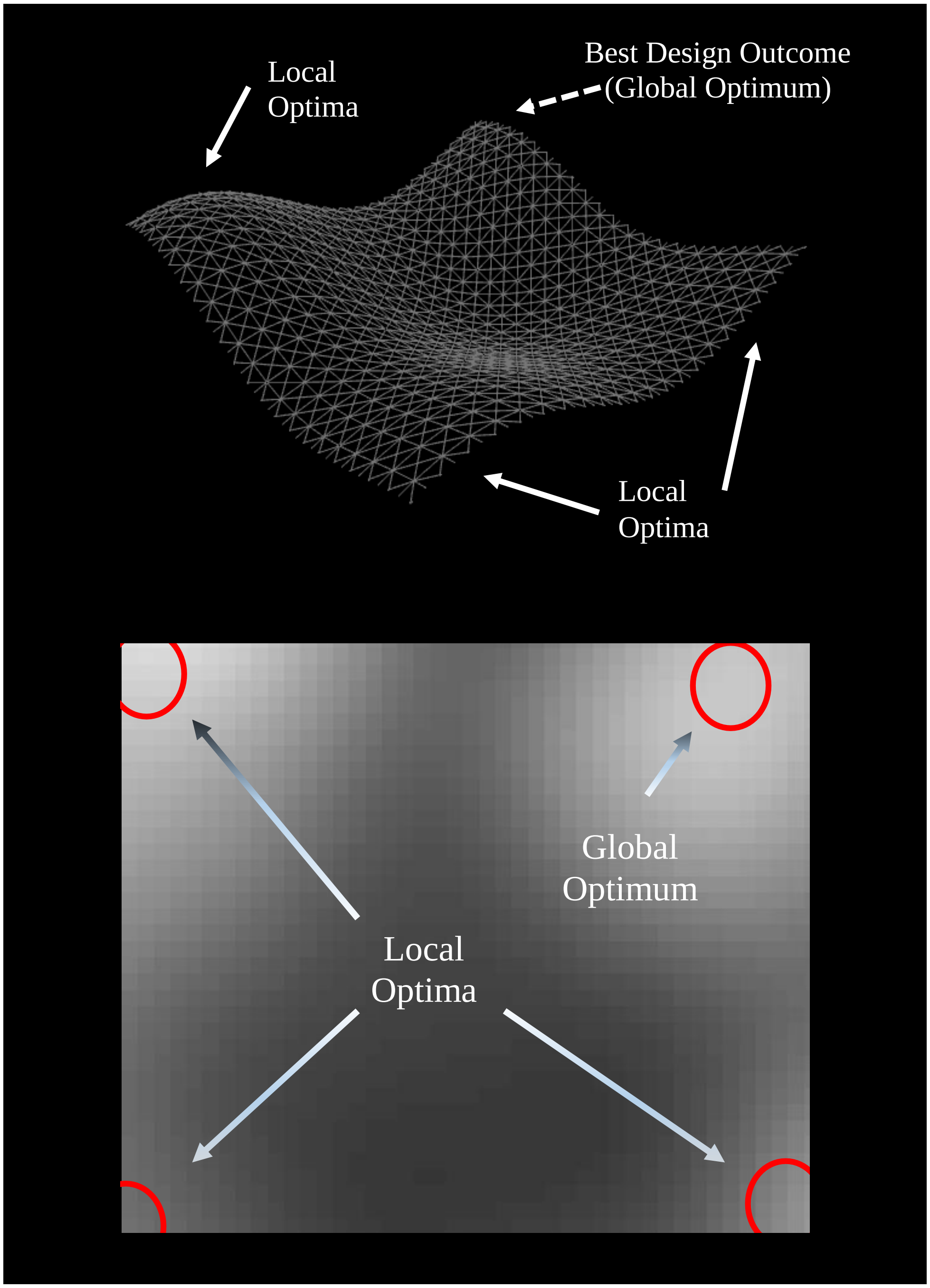


Figure 1.10 Design Landscape ($N = 10,\ K = 2.8$)

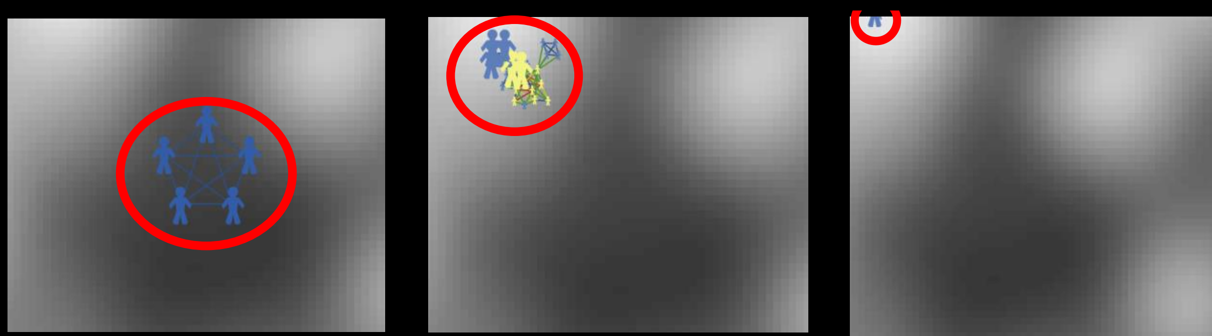
1.3.3 Design Collaborations

The research creates these fitness landscapes as not only a means of displaying complexity in a novel way, but because it enables the design management analyst to explore the search behaviors of the DAU under various degrees of complexity and using numerous strategies. The research remains particularly interested in how design-teams form and come together. The essential nature of engineering design represents a very elaborate collaborative *socio-technical* system. The research leverages fundamental research into team-formation and collaborations from Guimerà et al. (2005) to inform our research as well as to focus it. As a result, although many other team factors may exist, we look primarily at the following as a starting point for this research:

- the role of team-size;
- the willingness of team-members to incorporate new team-members;
- the preferences of team-members to repeat past collaborations; and,
- the maximum-downtime before past collaborators (i.e. incumbents) lose interest and no longer make themselves available to contribute to the collaboration.

Our collaborations, like those highlighted by Guimerà et al. (2005), form from teams. These teams assemble themselves at the start of each increment of time. As teams adopt newcomers and with time, the "invisible college" or the body of possible collaborations grows to a steady-state level depending on the combination of parameters addressed above. Previous team-members become incumbents within the collaboration, and provide a store of knowledge and support to the collaboration and its efforts. In the work by Guimerà et al. (2005), these dynamics remained separate from any search or adaptive actions. We however introduce these collaborative dynamics to the design landscape through the DAU and modify them to enable the collaboration to adapt to (i.e. explore) the landscape through the addition of natural selection and hill climbing mechanisms. We also expand on these parameters from Guimerà et al. (2005). For instance, we go past the willingness of teams to incorporate new team-members to explore the role that the degree of allowable diversity may have on the performance of the DAU (i.e. how far from the recruiting design-team member's own conceptual locus will he or she accept a new team member from). The research tests for the influence of these parameters in the ability of a DAU to come to a design resolution quickly and provides an extensible framework for many future explorations into the performance of design-teams and other collaborative decision-making groups. Figure 1.11

demonstrates the DAU collaboration as it adapts to the design landscape in search of a design solution and Figure 1.12 highlights the resulting final collaboration structure for the DAU.

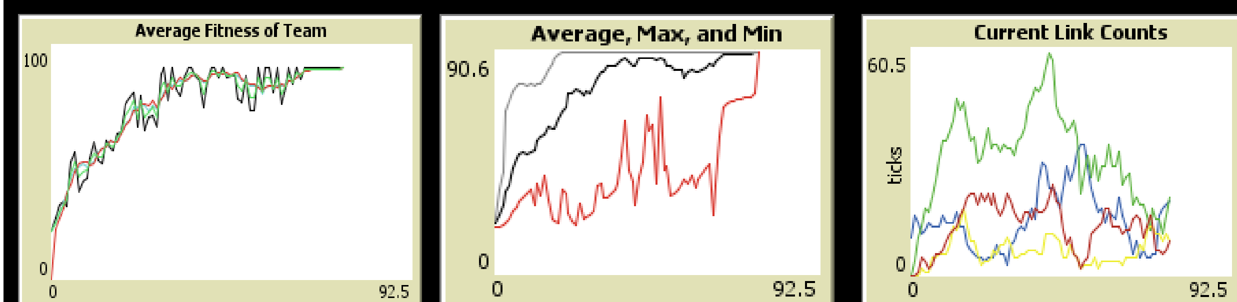


Initial Collaboration Forms with Wide Exploration

DAU Finds Fitness and Limits its Exploraiton

DAU Termiantes Search on Local Optima (at 75 ticks)

Time (ticks)



Average Fitness Measures for the DAU (colors refer to the particular measure, *i.e.* blue refers to the average fitness of the entire collaboration, black refers to the average fitness of the current design-team, red corresponds to the average fitenss of the incumbents, and green represents an average of both the performance of the collaboration and the team).

Min, Max, and Mean Fitness Plot for the DAU

Collaboration characteristics (colors refer to type of collaboraiton, *i.e.* blue a new-comer collaborating with a new-comer, red measures repeat collaborations, yellow measurse incumbent-incumbent collaborations, and green measures the number of newcomer-incumbent collaboratiosn).

Figure 1.11 Collaboration Exploring the Design Landscape and Sample Simulation Results

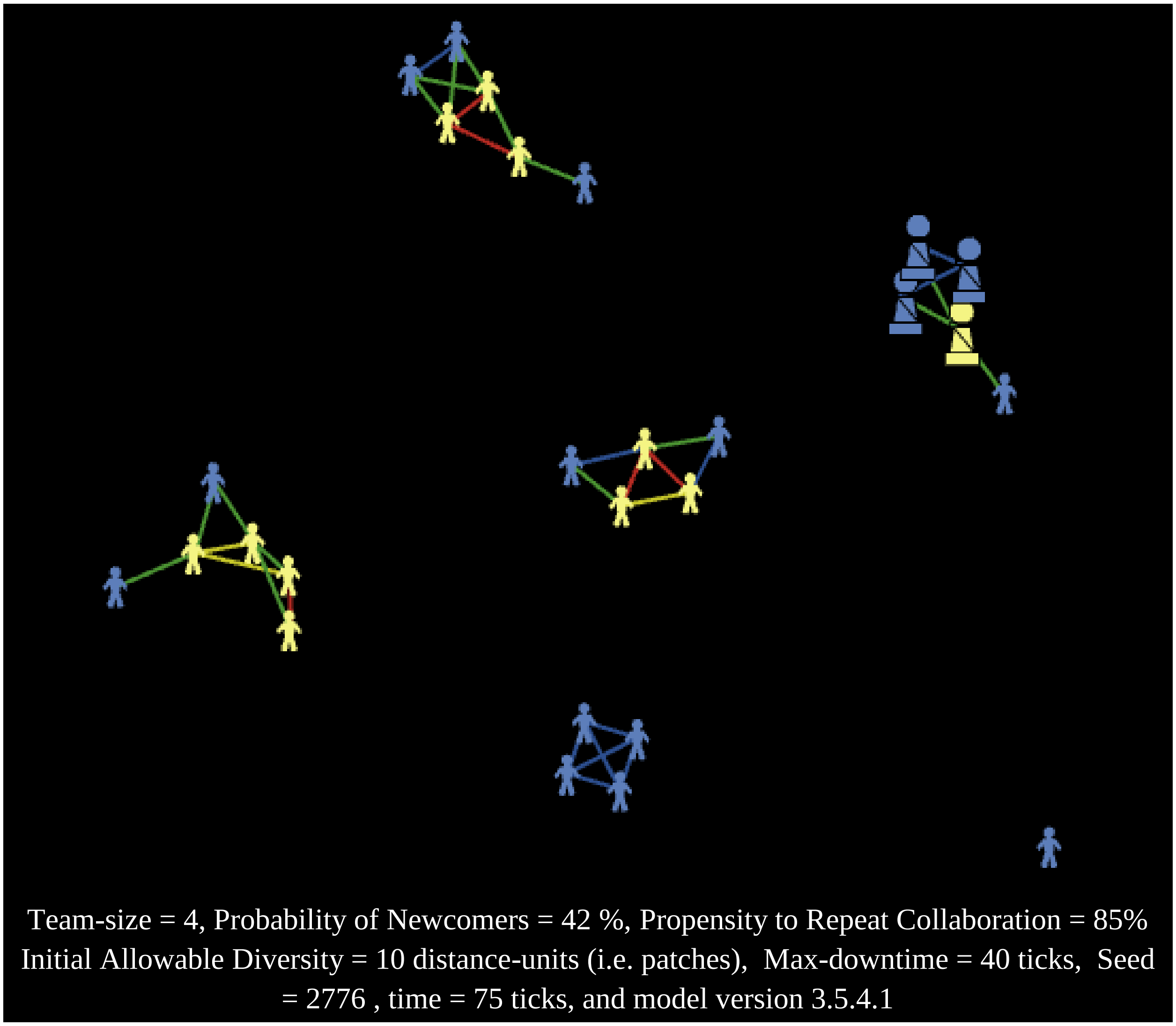


Figure 1.12 Sample Design Collaboration Network Structure at Last Tick of Exploration. We notice that that the design collaboration, under the parameter configuration used and for the given landscape, results in a largely disconnected collaboration with multiple clusters of designers. Although we mainly focus the performance of the DAU in achieving design objectives, we also capture characteristic network metrics for the collaboration. As part of each run, these metrics include capturing the clustering coefficient, the connectedness of the graph, as well as the average-max-min of the path lengths for each collaboration. In the above depiction, the pawn symbol represents a current-team member. The colors for these agents, similar to the colors of links discussed in the previous figure (cf. Figure 1.1.3), represents the type of agent. For example, blue agents represent newcomers to the collaboration, *i.e.* they have only participated in the design-team once. Conversely, yellow agents represent agents who have repeated multiple times. All agents qualify as 'incumbents' regardless of the number of times they have contributed to a design-team. However, the likelihood of inclusion on future design-teams does benefit from having worked with a selecting team-member in the past (based on the propensity of a team-member to work with colleagues he has worked with in the past over an incumbent with whom he has not previously engaged).

1.4 Research And Experimental Hypotheses

Based on the research objectives discussed, the following hypotheses attempt to relate the socio-collaborative team-dynamics, the techno-problem space, and the resulting performance of a design effort. The specific research hypotheses (i.e. alternative hypotheses) and null hypotheses follow:

Alternative Hypothesis 1: Varying the team-formation dynamics (i.e. the probability of incorporating a newcomer (p), the propensity of team-members to repeat collaborations (q), the overall team-size (n) embedded in the larger collaboration, and the maximum-downtime (mdt) for a previous collaborator) of a design-team leads to significant differences in the average design-team fitness values ($\overline{f_t}$) and the search time for the design-team (t_s).

$$\left|\frac{\partial \overline{f}_t}{\partial p}, \frac{\partial \overline{f}_t}{\partial q}, \frac{\partial \overline{f}_t}{\partial n}, \frac{\partial \overline{f}_t}{\partial mdt}\right| > 0 \quad \wedge \quad \left|\frac{\partial t_s}{\partial p}, \frac{\partial t_s}{\partial q}, \frac{\partial t_s}{\partial n}, \frac{\partial t_s}{\partial mdt}\right| > 0 \qquad H_{a_1}$$

Null Hypothesis 1: Varying the team-formation dynamics (i.e. the probability of incorporating a newcomer (p), the propensity of team-members to repeat collaborations (q), the overall team-size (n) embedded in the larger collaboration, and the maximum-downtime (mdt) for a previous collaborator) of a design-team does not lead to significant differences in the average design-team fitness values ($\overline{f_t}$) and the search time for the design-team (t_s).

$$\left|\frac{\partial \overline{f}_t}{\partial p}, \frac{\partial \overline{f}_t}{\partial q}, \frac{\partial \overline{f}_t}{\partial n}, \frac{\partial \overline{f}_t}{\partial mdt}\right| = 0 \quad \wedge \quad \left|\frac{\partial t_s}{\partial p}, \frac{\partial t_s}{\partial q}, \frac{\partial t_s}{\partial n}, \frac{\partial t_s}{\partial mdt}\right| = 0 \qquad H_{o_1}$$

Alternative Hypothesis 2: There exists an inverted U-shaped relationship between the likelihood of newcomers (p) on a design effort and the final design-team fitness (f_t).

$$\lambda\, p \;\approx\; -{f_t}^2, \quad \lambda = \text{constant scalar} \qquad H_{a_2}$$

Null Hypothesis 2: There does not exist an inverted U-shaped relationship between the likelihood of newcomers (p) on a design effort and the final design fitness (f_t).

$$\lambda\, p \;\not\approx\; -{f_t}^2, \quad \lambda = \text{constant scalar} \qquad H_{o_2}$$

Alternative Hypothesis 3: Increasing the level of diversity among newcomers (m) in the design-team has a positive relationship with the prevention of design fixation as measured by the ratio of the final fitness values of the design-team (f_t) to the global fitness maximum (f_m).

$$\left(f_t/f_m\right)\Big|_{m_1} \quad < \quad \left(f_t/f_m\right)\Big|_{m_2} \; for \;\; m_1 > \; m_2 \qquad\qquad H_{a_3}$$

Null Hypothesis 3: Increasing the level of diversity among newcomers (m) in the design-team does not have a positive relationship with the prevention of design fixation as measured by the ratio of the final fitness values of the design-team (f_t) to the global fitness maximum (f_m).

$$\left(f_t/f_m\right)\Big|_{m_1} \quad \nless \quad \left(f_t/f_m\right)\Big|_{m_2} for \;\; m_1 > \; m_2 \qquad\qquad H_{o_3}$$

Alternative Hypothesis 4: There exists a maximum team-size (n^*) before the marginal productivity of design becomes negative.

$$\frac{\partial P}{\partial n^*} > 0 \geq \frac{\partial P}{\partial n'} \; \forall \;\; n^* > n' \qquad\qquad H_{a_4}$$

Null Hypothesis 4: There does not exist a maximum team-size (n^*) before the marginal productivity of design becomes negative.

$$\frac{\partial P}{\partial n^*} = \frac{\partial P}{\partial n'} \; \forall \;\; n^* > n' \qquad\qquad H_{a_4}$$

Alternative Hypothesis 5: There is a statistically significant positive linear correlation between the fraction of newcomers (p) and both the search time (t_s) and average design-fitness values ($\overline{f_t}$).

$$t_s = \; \lambda p + \; \varepsilon \;\; \wedge \;\; \overline{f_t} = \; \lambda p + \; \varepsilon \quad \lambda = \text{slope}, \varepsilon = \text{constant} \qquad\qquad H_{a_5}$$

Null Hypothesis 5: There is not a statistically significant positive linear correlation between the fraction of newcomers (p) and both the search time (t_s) and average design-fitness values ($\overline{f_t}$).

$$t_s \; \neq \; \lambda p + \; \varepsilon \;\; \wedge \;\; \overline{f_t} \; \neq \; \lambda p + \; \varepsilon \quad \lambda = \text{slope}, \varepsilon = \text{constant} \qquad\qquad H_{o_5}$$

Alternative Hypothesis 6: There is a statistically significant negative correlation, using the Spearman correlation coefficient (ρ), between the propensity of a design-team to repeat a collaboration (q) and the average design-team fitness ($\overline{f_t}$), as well as search-times(t_s).

$$\rho = 1 - \frac{6\sum\left(q_i - \overline{f_{t_i}}\right)^2}{n(n^2-1)} < 0 \quad \wedge \quad \rho = 1 - \frac{6\sum\left(q_i - t_{s_i}\right)^2}{n(n^2-1)} < 0 \qquad q_i, f_{t_i}, t_{s_i} = ranks^{7} \qquad H_{a_6}$$

Null Hypothesis 6: There is not a statistically significant negative correlation, using the Spearman correlation coefficient (ρ), between the propensity of a design-team to repeat a collaboration (q) and the average design-team fitness ($\overline{f_t}$), as well as search-times (t_s).

$$\rho = 1 - \frac{6\sum\left(q_i - \overline{f}_{t_i}\right)^2}{n(n^2-1)} = 0 \quad \wedge \quad \rho = 1 - \frac{6\sum\left(q_i - t_{s_i}\right)^2}{n(n^2-1)} = 0 \qquad q_i, f_{t_i}, t_{s_i} = ranks \qquad H_{o_6}$$

Alternative Hypothesis 7: Varying the diversity of newcomers (m) to the design-team at each unit of time, using a saw-tooth wave function, when unfit improves search times (t_s) and the design-team final fitness values (f_t).

$$f_t|_{m(t)=t-\lfloor t \rfloor} > f_t|_m \quad \wedge \quad t_s|_{m(t)=t-\lfloor t \rfloor} < t_s|_m \qquad H_{a_7}$$

Null Hypothesis 7: Varying the diversity of newcomers (m) to the design-team at each unit of time, using a saw-tooth wave function, when unfit neither improves search times (t_s) nor the design-team final fitness values (f_t).

$$f_t|_{m(t)=t-\lfloor t \rfloor} \ngtr f_t|_m \quad \wedge \quad t_s|_{m(t)=t-\lfloor t \rfloor} \nless t_s|_m \qquad H_{o_7}$$

Alternative Hypothesis 8: Increasing the *maximum-downtime* (mdt) decreases the search time of the design-team (t_s).[8]

$$mdt \approx {}^{\lambda}/_{t_s} \qquad \lambda = \text{constant scalar} \qquad H_{a_8}$$

---

[7] Differences in paired ranks over n number of pairs of data determines the Spearman's Rank Correlation Coefficient.
[8] The maximum-downtime (mdt) equates to the allowable amount of time, measured in ticks, an agent of the larger collaboration can exist apart from the team without losing interest and leaving the collaboration.

Null Hypothesis 8: Increasing the *maximum-downtime* (mdt) does not decrease the search time of the design-team (t_s).

$$mdt \not\approx {}^{\lambda}/_{t_s} \qquad \lambda = \text{constant scalar} \qquad H_{o_8}$$

Alternative Hypothesis 9: There is a statistically significant negative correlation, using the Spearman's correlation coefficient (ρ), between the management and technical leadership pressure (λ_u) and the search-time for the design-team (t_s).

$$\rho < 0 \qquad H_{a_9}$$

Null Hypothesis 9: There is not a statistically significant negative correlation, using the Spearman's correlation coefficient (ρ), between the management and technical leadership pressure (λ_u) and the search-time for the design-team (t_s).

$$\rho \geq 0 \qquad H_{o_9}$$

Alternative Hypothesis 10: Selectively increasing management and technical leadership pressure (λ_u) leads to reduced search times (t_s) and decreased design-team final fitness values (f_t).[9]

$$f(\lambda_u, t) \,\tilde{\propto}\, {}^{1}/_{t_s} \;\wedge\; f(\lambda_u, t) \,\tilde{\propto}\, f_t \qquad H_{a_{11}}$$

Null Hypothesis 10: Selectively increasing management and technical leadership pressure (λ_u) neither reduces search times (t_s) nor decreases design-team final fitness values (f_t).

$$f(\lambda_u, t) \not\approx {}^{k}/_{t_s} \;\wedge\; f(\lambda_u, t) \not\approx k * f_t \qquad k = \text{constant} \qquad H_{o_{11}}$$

Alternative Hypothesis 11: Selectively eliminating the diversity of newcomers (m) reduces search times (t_s) and decreases design-team final fitness values (f_t). [10]

[9] Selectively increasing the management and technical leadership pressure (λ_u) as the design process matures (when the average team-fitness ($\overline{f_t}$) does not meet performance objectives) may improve the search-times for the design process by driving consensus and preventing the prolonged geographic isolation of team-members.

[10] Selectively restricting the diversity of newcomers (m) as the design process matures (i.e. decreasing diversity as the average team-fitness ($\overline{f_t}$) meets performance objectives) may improve the search-times for the design process.

$$f_t|_{m(t)} > f_t|_m \quad \wedge \quad t_s|_{m(t)} < t_s|_m$$
$$\forall\, t \mid \overline{f_t} > f_{objective}\colon\ m = 0 \ \ \wedge \ \ \forall\, t \mid \overline{f_t} \le f_{objective}\colon\ m = m_i \qquad H_{a_{10}}$$

[11]

Null Hypothesis 11: Selectively eliminating the diversity of newcomers (m) reduces search times (t_s) and decreases design-team final fitness values (f_t).

$$f_t|_{m(t)} \ngtr f_t|_m \quad \wedge \quad t_s|_{m(t)} \nless t_s|_m$$
$$\forall\, t \mid \overline{f_t} > f_{objective}\colon\ m = 0 \ \ \wedge \ \ \forall\, t \mid \overline{f_t} \le f_{objective}\colon\ m = m_i \qquad H_{o_{10}}$$

Alternative Hypothesis 12: There exists an inversely proportional relationship between search times (t_s) and the smoothness of the design landscape (S^*).

$$S^* \propto \frac{1}{t_s} \qquad H_{a_{12}}$$

Null Hypothesis 12: There does not exist an inversely proportional relationship between search times (t_s) and the smoothness of the design landscape (S^*).

$$\lambda S^* \not\approx \frac{1}{t_s}, \qquad \lambda = \text{ constant scalar} \qquad H_{o_{12}}$$

Alternative Hypothesis 13: Structuring the *design matrix* $[A]$ according to the *axiomatic rules of design* $[A]^*$ reduces the required search time for the design-team (t_s).[12]

$$t_s|_{[A]^*} < t_s|_{[A]} \qquad H_{a_{13}}$$

Null Hypothesis 13: Structuring the *design matrix* $[A]$ according to the *axiomatic rules of design* $[A]^*$ does not reduce the required search time for the design-team (t_s).

$$t_s|_{[A]^*} \nless t_s|_{[A]} \qquad H_{o_{13}}$$

[11] If the average fitness of the DAU falls under the objective fitness, this strategy resets the allowable diversity back to its initial value (m_i).

[12] The axiomatic approach towards design requires minimizing information content of a design and ensuring its functional independence, as discussed in Chapter 2. In our approach, these characteristics give rise to the complexity of the design landscape.

1.5 Summary and Organizations of Research

This first chapter briefly described the growing disconnect between normative approaches for design and an empirical body of evidence underscoring the failures of this approaches. The research also provided an archetypal example of an application of this research. The main points from this introductory discussion include:

- Two major approaches for dealing with complexity include the decomposition of the search space and, in the case of complex systems, the use of naturalistic search strategies;
- Despite efforts to reduce avoid, mitigate, and structure elements of complexity in design, the observed steady increase of complexity can be assumed to continue or accelerate in the future;
- Most currently prescribed design approaches fail to capture design as part of a complex designer-artefact-user system, neglecting critical *socio-technical* dynamics;
- Approaches towards the measurement of design performance predominately focus on characteristics of the final engineered artefact without providing context into performance relative to design as a process;
- New approaches toward design complexity management and performance evaluation require incorporating aspects of both structural technical complexity and the social dynamics involved in engineering design;
- Relationships between design elements, *i.e.* interconnectedness, seen in the design matrix provides insights into the inherent technical complexity of a task and give rise to the *design landscape*;
- The team formation dynamics govern the performance of design-team performance; and,
- The modelling of design-teams searching hypothetical *design landscapes* provide insights into performance that can help inform the development of strategies

The following chapters explore and build upon these points. In the following literature review, the research provides: an overview of the current schools of thought regarding traditional approaches toward design; a general summary of work focusing on the 'complexity crisis' facing engineering design; and some general background on complex adaptive systems. From there the literature review highlights work in collaborative dynamics, and provides a look at some initial related work at creating a complex adaptive design approach to complexity management from which the research builds. The remaining research divides along the lines of its major thrusts. These thrusts include examining engineering design from the perspective of collaborative design-teams; exploring technical complexity with *design landscapes*; and finally, through the unification of these aspects of engineering design into a direct performance evaluation approach through a model. The research then concludes with a discussion of the experiments runs and an overall discussion covering the research findings.

This remaining division for this work follows:

- Literature Review
- C^2D Conceptual Framework and Associative Inferences
- C^2D Model and Formulations
- Experimental Design and Approach
- Conclusions and Discussion

2

LITERATURE REVIEW

``Professors discussing Engineering Design are like Priests discussing marriage: lots of learned thought, but very little practical experience.''

- Professor David Gossard, MIT
NSF Design Conference, Amherst, MA, June 1989

The pertinent literature central to the problems and objectives associated with this research span multiple disciplines and research domains. Although the literature included as part of this review reflects a broad summary of the surveyed work, the review also focuses on design from the viewpoint of the practitioner. The following discussion provides the necessary and most relevant findings from the existing compendium of work. It is the goal of this chapter to provide the reader a basis for understanding the fundamental concepts underpinning this research and its findings. In order to provide this primer we individually discuss the building block of the *Complex Adaptive Performance Evaluation Method for Collaborative Design* (C^2D) model presented in the research:

- Engineering design as the collaborative process for creating new processes and systems;
- Complex adaptive systems thinking and its application to engineering design-teams;
- Fitness landscapes as representations of performance in complex spaces;
- Collaborative team-based dynamics and their drivers of performance; and,
- Performance efficiency measurement and design approaches

The research build on this background in the following chapters by presenting a unified framework and parsimonious model for experimentation, providing the design of experiments, and, finally, by adding to this theoretical background both confirmatory and unique insights.

2.1 DESIGN: AN ENGINEERING PERSPECTIVE

The concepts, tools, and methods of design remain critical to the research addressed. The word *design* persists after centuries of usage and carries multiple meanings across various professions, ranging from artists to engineers. We begin to distinguish our usage of the term by first examining the definition and origin of design. The *Oxford American College Dictionary* defines it as:

de·sign (/dəˈzīn/)

noun

noun: **design**; plural noun: **designs**

1. a plan or drawing produced to show the look and function or workings of a building, garment, or other object before it is built or made.
   "he has just unveiled his design for the new museum"
   synonyms: plan, blueprint, drawing, sketch, outline, map, plot, diagram, draft, representation, scheme, model
   "a design for the offices"

   - the art or action of conceiving of and producing a plan or drawing.
     "good design can help the reader understand complicated information"

   - an arrangement of lines or shapes created to form a pattern or decoration.
     "pottery with a lovely blue and white design"
     synonyms: pattern, motif, device; style, composition, makeup, layout, construction, shape, form

2. purpose, planning, or intention that exists or is thought to exist behind an action, fact, or material object.
   "the appearance of design in the universe"
   synonyms: intention, aim, purpose, plan, intent, objective, object, goal, end, target, hope, desire, wish, dream, aspiration, ambition

verb

verb: **design**; 3rd person present: **designs**; past tense: **designed**; past participle: **designed**; gerund or present participle: **designing**

1. decide upon the look and functioning of (a building, garment, or other object), typically by making a detailed drawing of it.
   "a number of architectural students were designing a factory"
   synonyms: plan, outline, map out, draft, draw

   - do or plan (something) with a specific purpose or intention in mind.
     "the tax changes were designed to stimulate economic growth"
     synonyms: intend, aim, devise, contrive, purpose, plan, tailor, fashion, adapt, gear, mean, destine

Origin: late Middle English (as a verb in the sense 'to designate'): from Latin designare 'to designate,' reinforced by French désigner. The noun is via French from Italian.

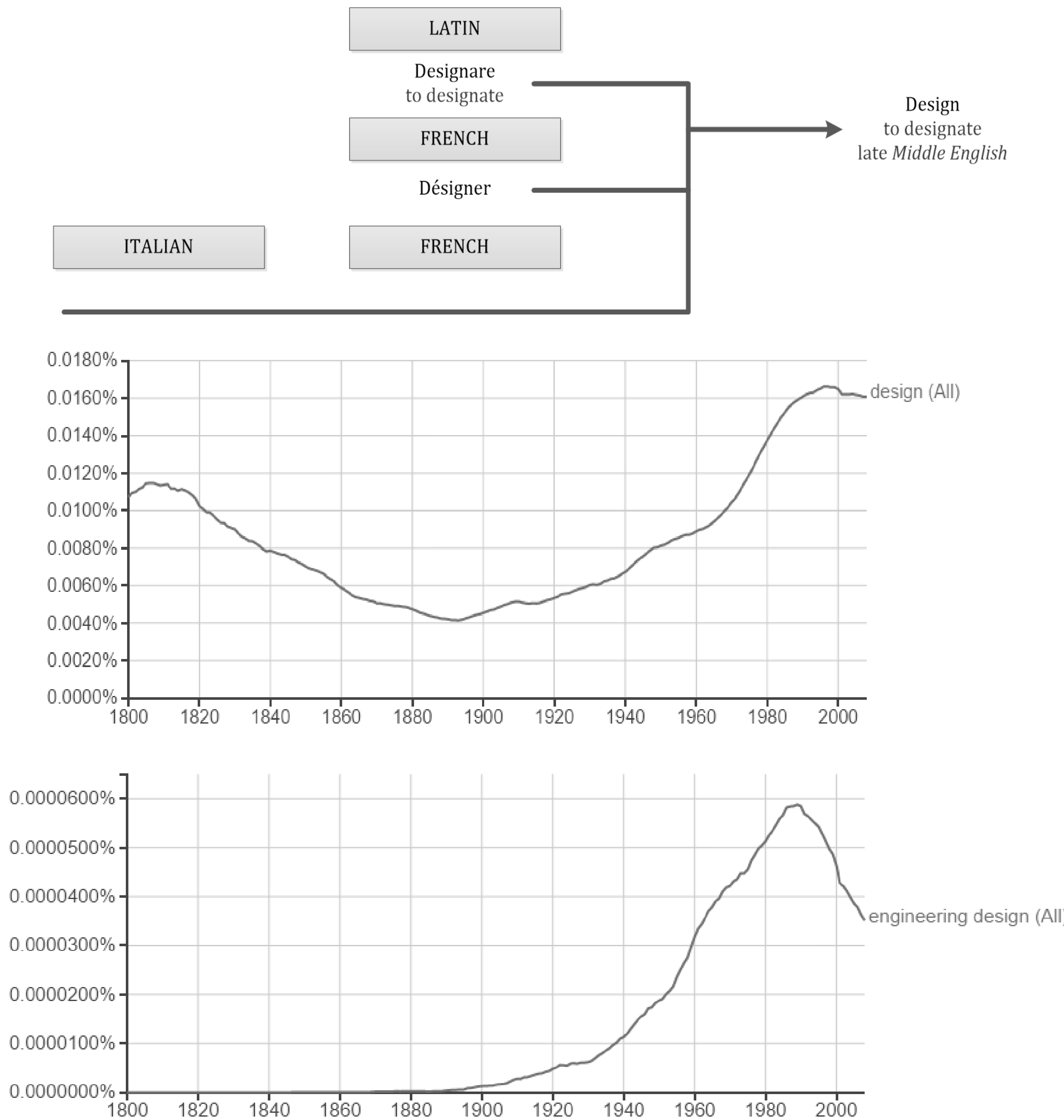


Figure 2.1 Word origins adapted from the *Oxford American College Dictionary* (2004) for *design* (top); and*,* English word usage statistics for both *design* (middle) and *engineering design* (bottom) from 1800 to 2008 using the © 2013 Google books Ngram Viewer tool (surveys use percentage over all electronically catalogued book holdings within Google). The vertical axis for the provided word statistics corresponds to the percentage of all words and the horizontal axis corresponds to time by annum.

At the core of these definitions rests the *purposeful process of reconciling form and function*. The word design remains at its most popular in the present-day. Figure 2.1 demonstrates both the word origin leading to its current form and its English usage statistics over the past two centuries, as well as engineering design in particular. Until the industrial era, *design* represented an expression of art more than science. Renaissance men such as Leonardo da Vinci encapsulate the essence of designers from this bygone era. However, recent applications of design have favored scientific and analytically based approaches.

Unlike designers of the past, their contemporaries must now work as parts of large multi-disciplinary *design-teams* in order to meet the complex design objectives they currently face. The increased need for overcoming technical complexity during beginning of the twentieth century lead to the differentiation of engineering design from design. As a result, *engineering design* represents a much more recent emergence in the lexicon; nevertheless, it has provided the fundamental process for engineers transforming needs and wants into solutions for over a century. This essential differentiation from the broader definition of *design* centers on its scientific and engineering basis for problem solving. Based in part on Pahl, Beitz, Feldhusen, and Grote (2007), we define *engineering design* as:

en·gi·neer·ing de·sign (/enjəˈni(ə)riNG dəˈzīn/)
noun
noun: **engineering design**; plural noun: **engineering designs**

1. the purposeful application of scientific **and** engineering knowledge to the solution of technical problems, including the optimization of solutions within the requirements and constraints set by material, technological, economic, legal, environmental and human-related considerations.

The process of *engineering design* takes on varying characteristics over its course; it begins as a highly abstract and conceptually based process, and it progresses with the gradual solidifying of the problem statements and design objectives. This ongoing process requires continuous task clarification and re-definition of the problem statement. Within the lexicon of modern systems engineering, these clarified tasks (*e.g.* requirements) help to specify the design problem and define the breadth of decisions available to the decision maker, *i.e. designer*. The resulting solidified problem descriptions also allows the application of progressively rigorous analytical tools to arrive at a detailed design. This overall process pulls deeply from both the creativity and analytical skills of the designer. As such, this process represents a nexus of these two intersecting domains, described as cultural and technical streams in the literature (Dixon 1966; Pahl 1984; Pahl et al. 2007; Griffin 2007; and, Lamb 2008). This work adopts this perspective of design as a team-based *socio-technical* process between designers, artefacts, and users. Figure 2.2 highlights design as an intersection of both technical and socially dynamics.

For purposes of the research, we represent this general process of *design* as equivalent to the search of an abstract conceptual space, *i.e.* the design landscape. Additionally, shown later in the chapter, we view the process of design and DAU system as a complex adaptive system. Although the research focuses on the conceptualization of a product in the context of the functional and physical domains of design (i.e. functional requirements and design parameters), much of the presented approach remains extensible to the process domain of design (i.e. process variables) and the corresponding practitioner, the production engineer.

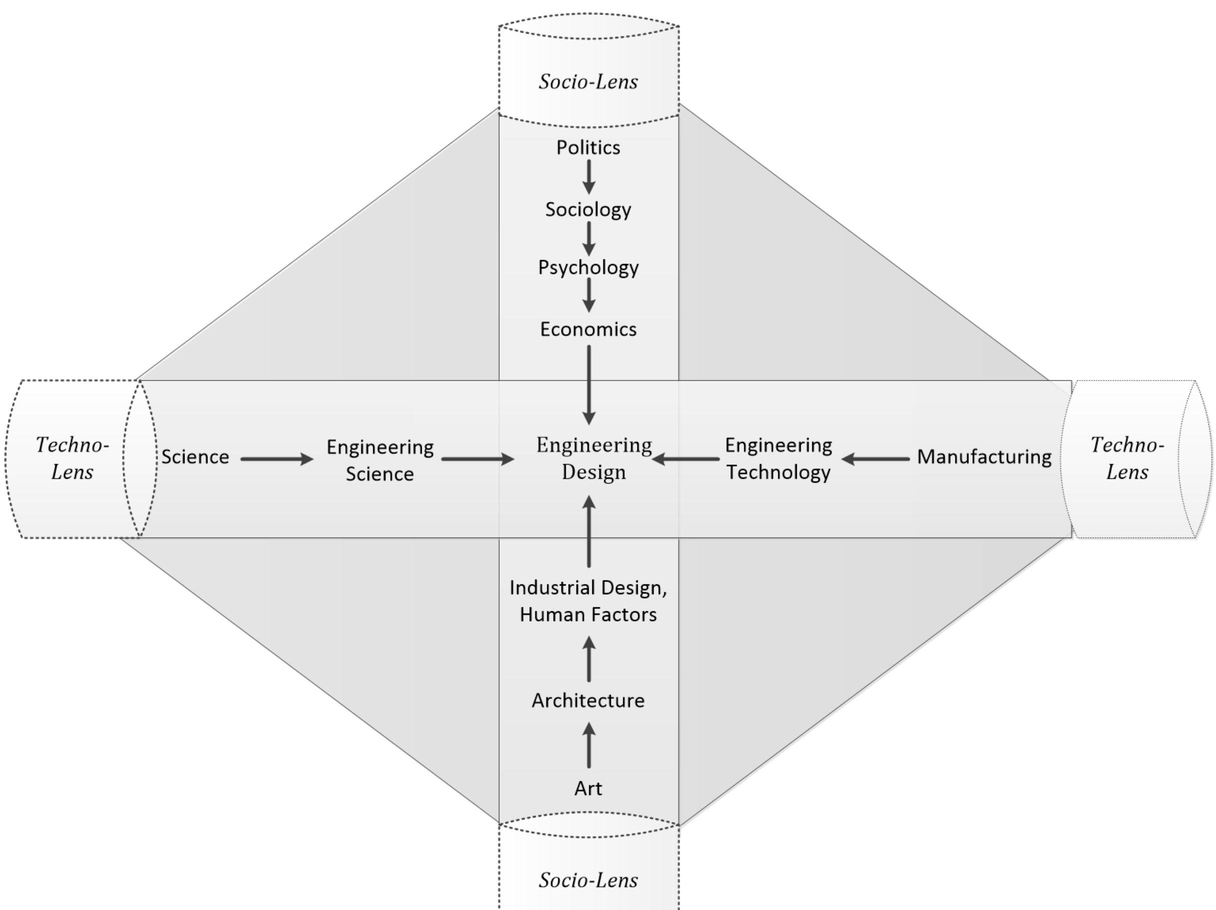


Figure 2.2 Examining *Design* as the Intersection of Two Perspectives. This figure shows design at the crossroads of –*techno* and –*socio* viewpoints. We adapt this figure from Pahl, Beitz, Wallace, and Council (1984) and Pahl et al. (2007) and after Dixon (1966).

The proceeding discussion of design helps to characterize many of the essential aspects of design, to include its:

- Widespread impact on almost all facets of human life;
- Ability to create perpetual novelty (i.e. original designs) and adapt previous works;
- Reliance on the laws and insights derived from the sciences to problem-solve;
- Common utilization of systematic approaches, such as the axiomatic approach;
- Critical role in the product life cycle, to include controllable costs;
- Dependencies on complex *socio-technical* dynamics;
- Capacity to build upon the experiences gained by *designers*; and,
- Role as the prerequisite for the manifestation of conceptual solutions

We provide these characterizations through the following design overview:

- Design as an engineering process;
- Axiomatic approach for design; and,
- Design as an experiential based collaborative socio-technical system

2.1.1 Process View of Engineering Design

The literature offers many perspectives on the way an engineered system comes into existence. Multiple models of the design process exist from the field of engineering design, including those found in the works of Jones, 1970; Cross, 1983; Roozenburg and Eekels, 1995; Baxter, 1995 and Field, 1995. Although many aspects of design remain highly sui generis, after a retrospective review across multiple design efforts, four key phases of activities emerge in the literature across the design process as a whole (Bonollo 1993; Bonollo and Lewis 1996; Hales and Gooch 2004; Blessing and Chakrabarti 2009). These phases include *task clarification*, *conceptual design*, *embodiment design*, and *detailed design*. The literature generally represents these phases of design as highly iterative and non-linear.

For purposes of illustrating the design, process, we adopt a generalized model of design that incorporates these phases and builds upon them by embedding verification into the process and by including design communication as a pivotal role in the design process. Although not commonly distinguished as its own iterative stage, design communication remains an essential element to the success of any design. This stage allows the design-team to solicit feedback and communicate results of the design-effort effectively with users and other stakeholders. This process provides a key mechanism in building beneficial design experiences. Figure 2.2 overlays a modified block diagram of the design process from French (1999) with the design phases discussed in the literature. The resulting meta-model based from the literature includes the following major design steps:

- task clarification;
- conceptual design and concept generation;
- evaluation, refinement, and verification;
- embodiment design;
- detailed design; and,
- design communication

During these phases of design, the design-team consistently interacts with both internal and external stakeholders to understand user needs, the available technologies for transforming these needs into products, and the environment in which they operate. These phases occur with iterative feedback, *i.e.* verification, between both the embodiment design, conceptual design, and task clarification phases. For simplification, we embed the verification role as an ongoing process that occurs throughout the design process.

2.1.1.1 Task clarification: specification of problem and requirements

Task clarification is the first phase of the design process and includes working with the client and/or stakeholders, *e.g.* managers, to come to agreement around a set of objectives that can inform the development of functional requirements. The first step includes working with the client to create a documented understanding of client needs. An initial design brief provides a description of the user needs sufficient to fulfill this purpose; this briefing should provide understanding of the context of the problem and some indication of requirements, without constraining the design (Norman 1990). The subsequent steps helps bound the problem by drawing on multiple sources of information, including from the literature, experts, standards, and regulations. According to Baxter (1995), this information search generally focuses on understanding the customer demands through market need research, the technological and manufacturing opportunities through technology audits, and the existing competing technology solutions through competing product analysis.

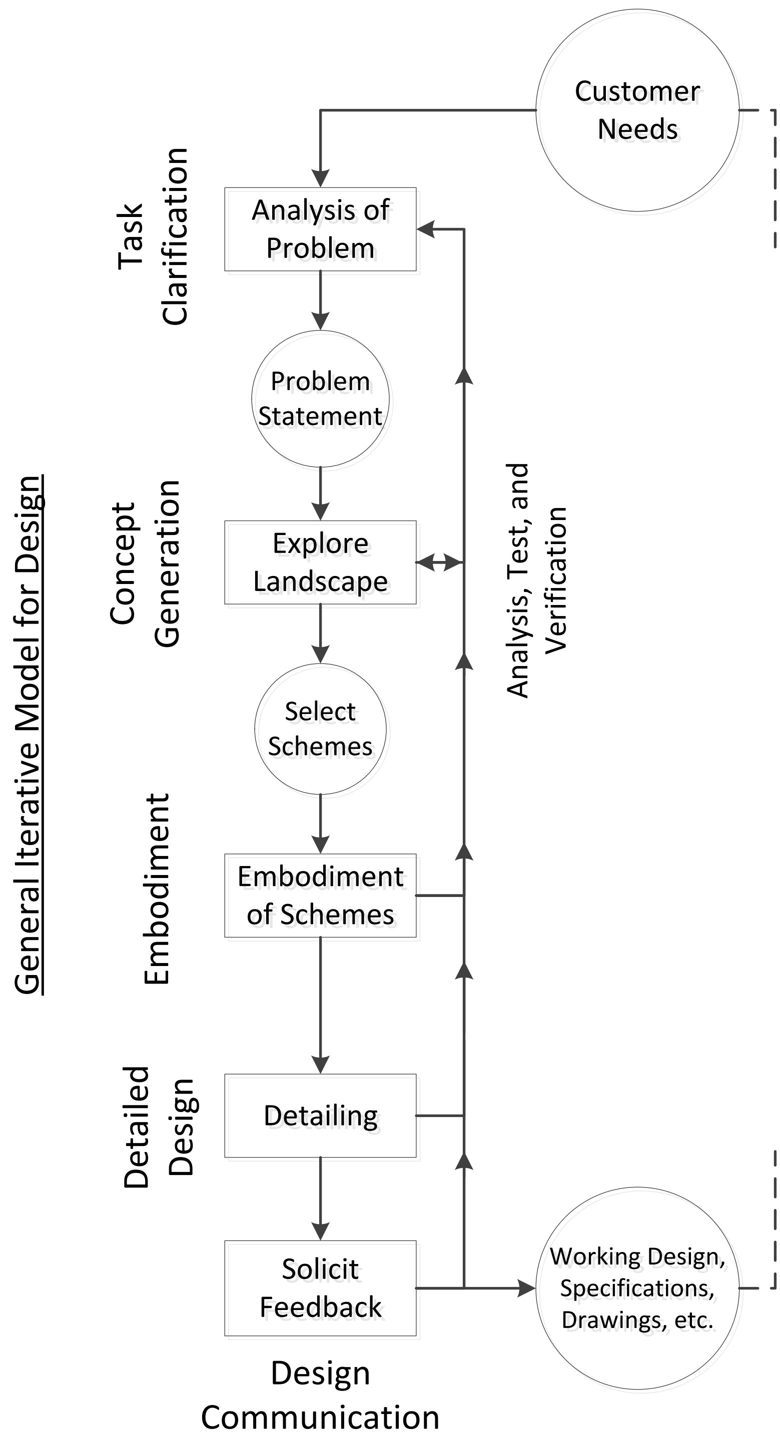


Figure 2.3 Phases of Engineering Design. This figure reviews the process of engineering, which spans multiple characteristic activities that generally fall into four major phases. These phases include *task clarification*, *conceptual design*, *embodiment design*, and *detailed design*. This diagram is adapted from concepts discussed in the design modelling work of French (1999) and from the theory of design in the literature (Bonollo 1993; Bonnollo and Lewis 1996).

After having the opportunity to review the available information and the context of the design problem, the next phase for task clarification phase generally focuses on brainstorming some initial ideas and engaging with the client. This general means providing the client an initial specification, *i.e.* list of normative statements about the desired properties for the design (Roozenburg and Eekeels 1995). This should help minimize any discrepancies between client and design objectives. Reaching an agreed to set of objectives for the design effort means involving the designers early, including in the upfront administrative work such as negotiating a briefing with the client (Goslett 1980). This early engagement helps to similarly limit disconnects between the client and designer by providing the design-team an improved understanding of the needs and contextual requirements of the stakeholders and potential users. After setting the design objectives, the design-team must also help to establish plans and schedules, survey available information, and support the development of a cost and schedule estimate to the client (Bonnollo and Lewis 1996). The establishment of these design objectives and initial requirements, when mapped to the current technology possibility space, gives rise to a theoretical design landscape. This design landscape describes the theoretical region of all feasible design solutions for the designer to explore; designers proceed from this initial phase by exploring this space as part of the conceptual design phase.

2.1.1.2 Conceptual design: search activities of design landscape

The concept generation phase and design phase follows from an understanding of the design problem and its context, acquired during the task clarification. During this phase, the designers generate ideas and explore the design landscape to identify design solutions. Figure 2.4 depicts how the conceptual design process gradually acquires new information to reduce uncertainty, with the goal of honing in on possible design solutions. The design-team performance during this phase often shapes the likelihood of success for each subsequent design phase; commonly the success during this phase often provides a core indicator for the relative likelihood of success for the overall effort, especially in new product development (Alger and Hays 1964; Baxter 1995; Roonzenburg and Eekels 1995; French 1999). Lifecycle cost emphasized by Buede (2011) and engineering change costs acquired from Cloud, Griffen, Larson, and Swan (1999) validates this perspective. Figure 2.5 graphs the same data, showing that the conceptual design phase caries the largest cost advantage, *i.e.* approximately one to eleven, for costs incurred versus compared to future costs committed.

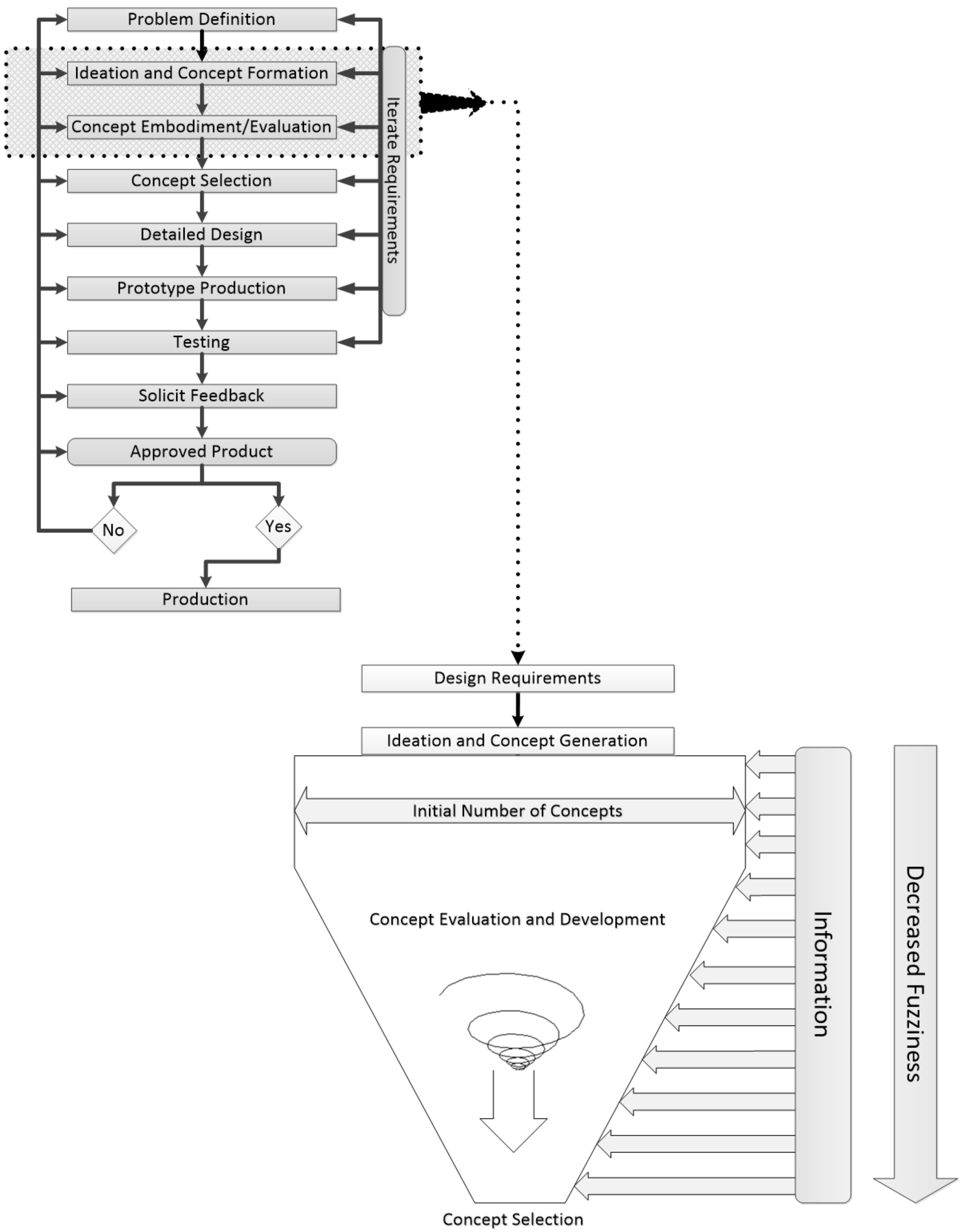


Figure 2.4 Conceptual Development and Evaluation Process. This diagram depicts the process of design as one that works towards reducing fuzziness in design (i.e. uncertainty), increasing understanding through new information, and moving (e.g. spiraling) towards a design solution.

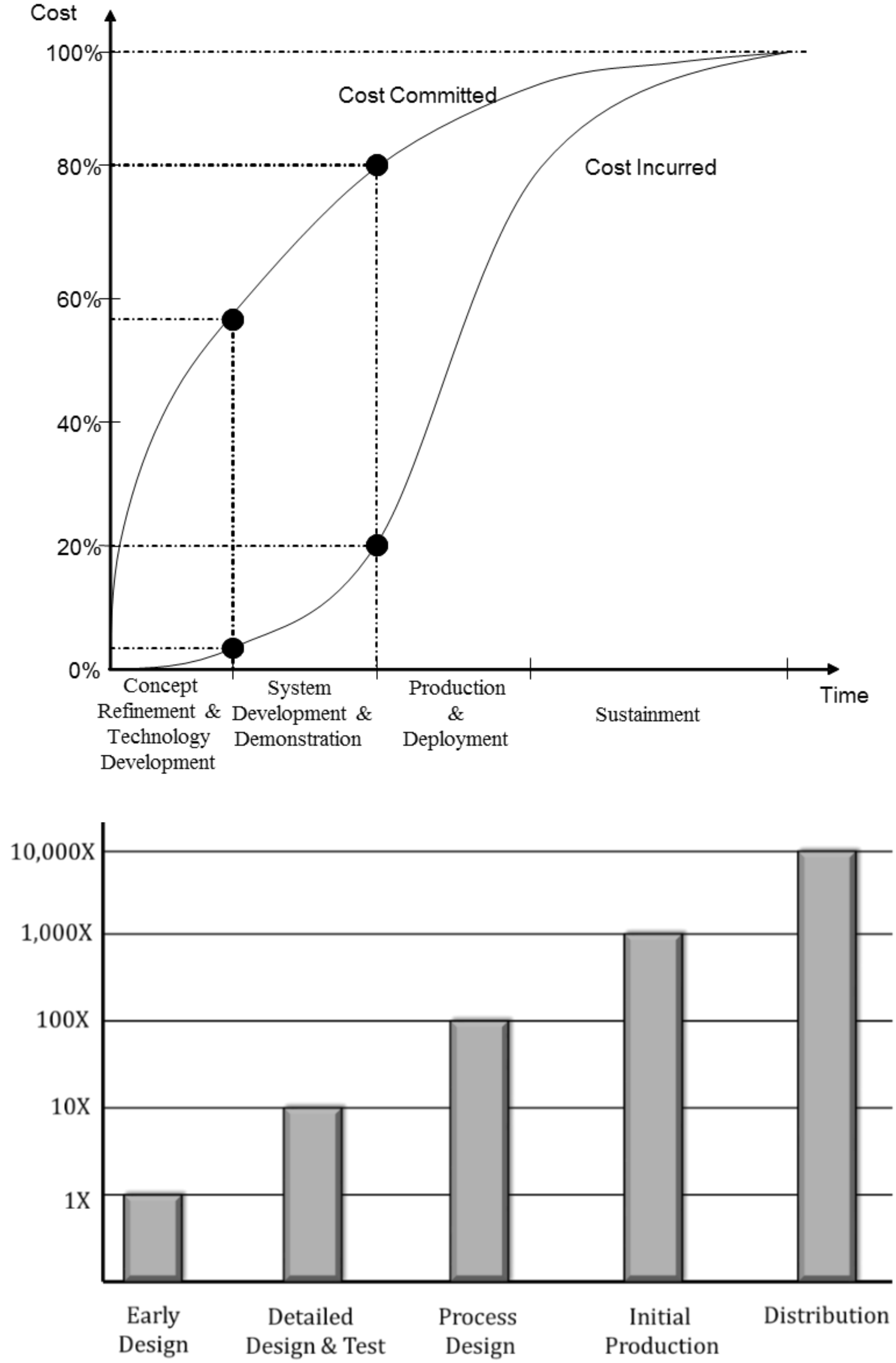


Figure 2.5 Comparison of Costs Committed Versus Incurred and Costs of Changes in Design Lifecycle. The early design processes for an engineered system has an inordinate influence on the lifecycle costs and performance of an engineered system. Reproduced with rights from John Wiley and Sons, data collected by Buede (2010) provides a comparison of the typical cost committed versus cost incurred at different points of the design lifecycle (top). Similarly, data acquired from Cloud et al. (1999) demonstrates the magnitude of difficulty and costs associated with introducing changes to a design as the design progresses through its development cycle using space-mission systems design cost data across several programs (bottom).

In order to navigate the exploration of this design space, the designer continually takes the statement of the problem and generates broad solutions to it in the form of possible schemes. These schemes represent locations in the design landscape that the designers focus their exploration. This effort carries the largest component of taxing mental work found throughout the design process, drawing heavily on the broad expertise (e.g. engineering science, practical knowledge, production methods, and commercial aspects, human factors) of the design-team (French 1999). In short, this process relies on the designer mapping abstract concepts into viable design concepts. The designer may use tools such as the house of quality (i.e. a method to identify critical customer attributes and to create a specific link between customer attributes and design parameters) or morphological charts (i.e. a method of mapping varied component solutions with respect to a set of design parameters); however, no clear methodological solution applies universally in this process.

This research focuses particular attention on the conceptual design phase as it stands out as one of the most important opportunities in influencing outcomes and in bending the cost curve for a design effort. The research asserts that this phase of design remains the most critical for design complexity, representing the best opportunity for the reduction of unnecessary and negative forms of system complexity. After this concept generation, the designers begin to embody their design schemes with physical characteristics.

2.1.1.3 Embodiment design: giving shape to the completed conceptual design

The embodiment design phase, sometimes referred to as the preliminary design phase, transforms conceptual schemes produced in the concept generation phase into potential design solutions. These potential design solutions consist of realistic design parameters, *i.e.* measurable and physical (to include software) characteristics of the design that satisfy functional requirements. Using qualitative rules that stress clarity, simplicity, and safety, this process molds the conceptual schemes into potentially manufacturable systems. These rules guide the materials and process requirements, e.g. the development of a system layout, a preliminary geometric design that specifies component shapes and materials, and the preliminary manufacturing and assembly concept for a design. Kesselring (1954) first introduced this concept and established a set of accompanying basic principles concerning minimizing manufacturing costs, minimizing requirements, minimizing weight, minimizing losses, and optimizing handling.

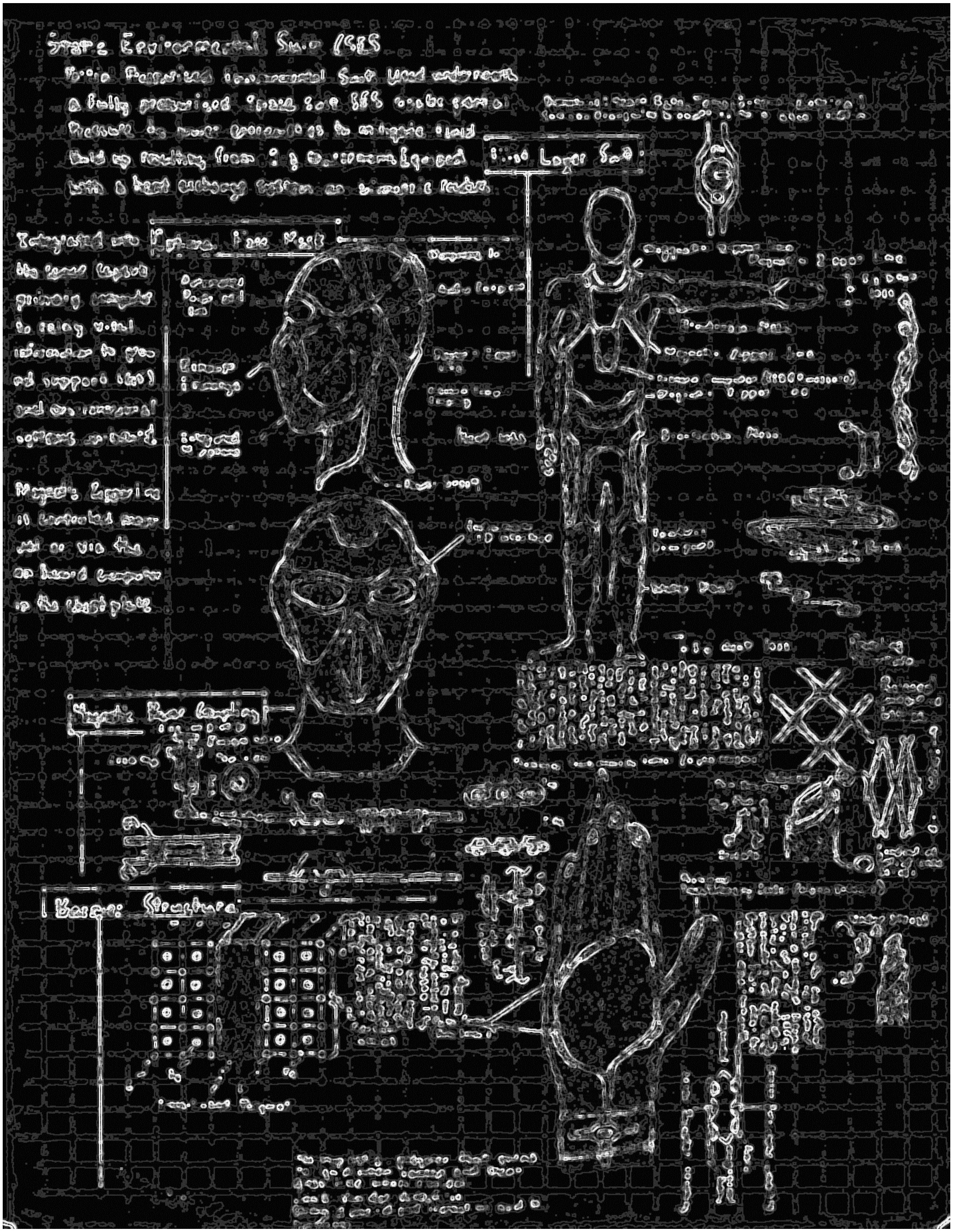


Figure 2.6 Spacesuit Embodiment Design Example. This figure is an example of early embodiment design in the creation of a space suit design by Swearson and Ambler (2009), details removed to ensure reproducibility of work.

These principles continue to guide determinations surrounding the feasibility of a design concept with regard to its production, its technical merit, and its economic considerations. Associated metrics surrounding these principles (e.g. weight, power, cost-per-unit) remain essential in establishing verification criteria during the design process. As this phase progresses, the additional design detail gives rise to a principle solution, or, in the event of more than one competitive design concept, multiple solutions. However, prior to advancing to a design decision, refinement of the analysis and requirements continue as part of the iterative design process of problem and solution redefinition (cf. Section 2.1.1.5). Designers during this phase typically rely on rules of thumb, simple models, known relationships between design parameters and outputs.

Part of this process may involve the creation of a prototype or initial simulation that undergoes rigorous testing and verification. The literature defines prototypes as any representation of a design concept, regardless of the medium (Houde and Hill 1997). The literature supports tightly relating and coupling this process to the conceptual design phase due to the large degree of feedback between the phases (French 1999; Langeveld 2011). Prototypes during this phase provide a benchmark or standard of measure for future design iterations. Prototyping during this phase occurs at a functional modelling level, *i.e.* the prototype captures key functional features and underlying operational principles. According to Houde and Hill (1997), the prototypes during this design phase generally fall into the following types and have the following questions:

- role prototypes; and,
    - *Does the design meet functional requirements?*
- look and feel prototypes
    - *Does the user accept the sensory inputs associated with the artefacts?*

These prototypes eventually mature with the overall design process into implementation based prototypes that examine the details of a design, and, finally, into integration prototypes that examines the various aspects of each type of prototype. This final integration prototype allows the design-team to communicate its results and final design concept prior to production.

2.1.1.4 Detailed design: finalizing the design Prior to Production

During the detailed design phase, the finalization of a large number of smaller but essential points occurs. In short, this phase establishes the part properties (e.g. dimensions, material composition, tolerances, geometric tolerances, surface roughness, number of final parts in overall system) and ideally eliminates any remaining uncertainty from the conceptual design. The literature defines the criteria for this phase as having sufficient fidelity (i.e. sufficient selection of parts and components) to accurately predict the eventual performance of system, typically through engineering and mathematical models (Ertas and Jones 1996). This activity includes the division of the conceptual design into its constituent elements (i.e. decomposition into subsystems, subunits, and component parts); the analysis, validation, and refinement of the concept; and, the final prototyping and evaluation testing of component parts, subunits, and the overall system. Prototyping in this phase general focuses on the implementation and integration of models, including various assembly models, production models, and, service models. Typically, designers use tools such as Computer Aided Dynamic Design (CADD) programs in creating and documenting these final designs. Engineers in this phase spend most of their effort focusing on preparing for formal reviews, complying with design codes, following handbooks, meeting applicable regulations, and incorporating supplier and manufacturing considerations into their design.

2.1.1.5 Iterative nature of design

As discussed, these phases of design remain highly iterative and nonlinear. Moving between the phases relies on iterative exchanges between the design-team, the user, stakeholders, and the environment (including technology). The design process first translates customer needs (i.e. attributes) into a set of functional objectives and requirements during task clarification; this approach allows the design-team to understand on functional level what must occur in order to meet these needs. After understanding these requirements at a functional level, the design-team must then relate which conceptual design parameters in a physical realm could help meet those functions. As seen in these design phases, the design-teams work to gradually transform user needs into increasingly refined requirements and design parameters that specify a physical mechanism to meet those requirements. Throughout this design cycle, the design-team continually monitors, tests, verifies, and validates the design parameters ability to meet the requirements. Figure 2.7 provides a depiction of these dynamics in the design process and provides a functional reasoning depiction demonstrating the nature of the process as an ongoing iteration between the problem redefinition and solution redefinition. Figure 2.8 demonstrates the design process at a high level using the example of a design requirement for a grain reaper. This overall process occurs across all four domains of design; we adopt these domains from the principles of axiomatic design subsequently discussed.

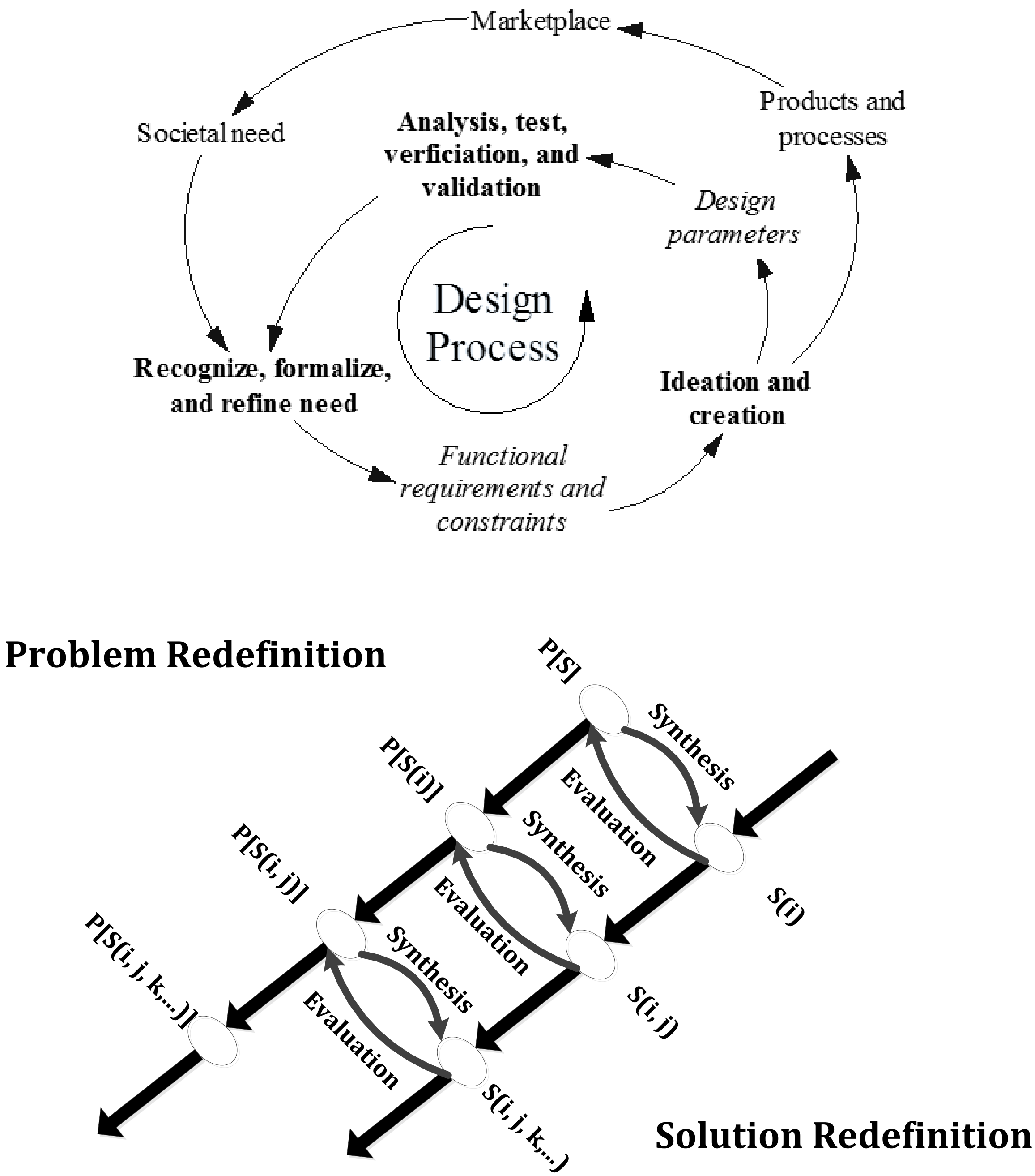
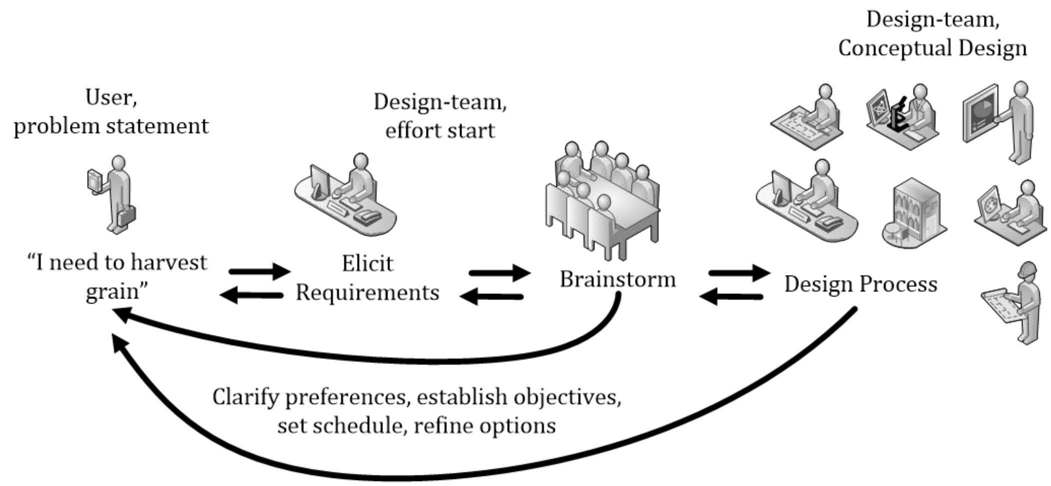


Figure 2.7 Design Process and Rational Iterative Model of Continuous Problem Solving. Design represents an intricate process of recognizing needs, formalizing those needs into requirements, conceptualizing solutions, testing the viability of those concepts, and finally refining the design before releasing it into the market. This process of analysis (e.g. formalize needs into requirements), synthesis (e.g. complete idea and optimize design decisions), and evaluation (e.g. exploration) occurs in a wider context of the marketplace (top). This process follows a rational iterative model of problem solving using a continuous problem and solution decomposition technique (bottom). This rational model depends on the ability of the designer to continually create conceptual solutions (i.e. synthesis) and evaluate their effectiveness (i.e. evaluation).

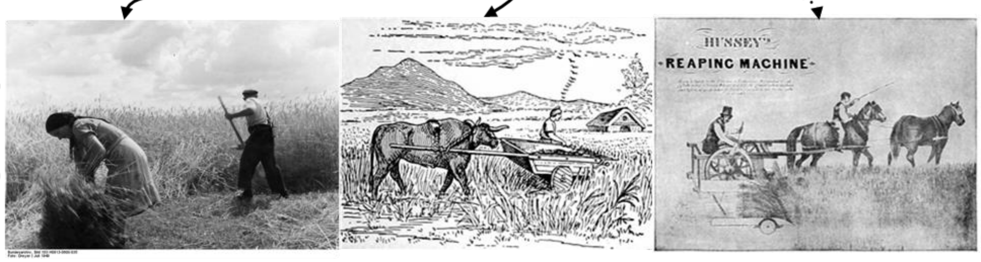


Evaluate options

FUNCTION	SOLUTION PRINCIPLES		
Supply energy to cut	Human	Horse	Petrol
Move device	Human	Horse	Tractor
Cut grain	Scythe	Cutter bar having fingers reciprocated by knife	Circular saw
Convey grain	Hand carry	Canvas	Pair of rollers
Store grain	Bundle and carry	Cart	Cart

D (Späth Chr 2006)

Design Concepts



A (Dreyer 1949) B (Unknown 1905) C (Unknown 1912)

Assign Value

		Weighted Values (100 points distributed)			
Criteria	**Weighting**	**Option A**	**Option B**	**Option C**	**Option D**
Maneuverability	0.5	3	7	10	20
Weight	0.1	6	-2	-3	-4
Appearance	0.1	-3	-1	-1	2
Price	0.1	4	0	0	-2
Cut Speed	0.1	-5	5	7	24
Robustness	0.1	1	7	10	15
	Totals:	6	16	23	55

Figure 2.8 Examples of Conceptual Design Process and Approach. An initial contact with the client provides the context and needs for design, which the designers work to transform into requirements. These requirements then, when mapped to possible solutions, give rise to ranked schemes. All embedded images in the figure are reproduced from the public domain and include citations.

2.1.2 Axiomatic Approach Towards Design

Axiomatic design, as described by Suh (1990), provides an overarching theoretical basis for design built on best practices observed in design. In this approach, design remains an ongoing iterative process, as described; however, it occurs across multiple domains, specifically the *customer domain*, the *functional domain*, the *physical domain*, and the *process domain*. The overall axiomatic framework defines a set of descriptions or characteristics of each of its domains. It defines *functional requirements* {FRs} as the minimal set of independent requirements in the functional domain necessary to characterize completely the *functional needs or customer attributes* {CAs} in the customer domain. Similarly, this framework defines *design parameters* {DPs} as the key physical attributes and variables in the physical domain that satisfy the functional requirements. Finally, the framework defines *process variables* {PVs} as the key variables in the manufacturing domain that produces the physical design. During the design process of problem and solution redefinition, the design-team must constantly navigates between these different distinct domains of a design. For example, the conceptual design phase most commonly operates by iterating between the functional domain and the physical domain. Suh (1990) refers to this iterative back and forth as zigzagging between the domains of design. Within this framework, as a design progresses and matures a phase transition occurs when the focus of the designers shift. For instance, as functional requirements solidify, interactions between the customer and functional domains gradually recede in favor of interactions between the physical and functional domains.

This axiomatic approach for design also leverages well-accepted best practices to deduce fundamental governing rules for these movements between domains; these two fundamental axioms of good design govern the axiomatic design theoretical basis. These axioms include that functional requirements must remain independent, and that an optimal design contains the minimal information content necessary to meet these requirements.[13] Figure 2.9 and Equation 2.1 adapts the representations of these domains from Suh (1990) to the characteristic phases of design.

[13] Importantly, independence of requirements does not dictate physical independence, *i.e.* distinctly separate physical manifestations, to satisfice requirements. In other words, a single component can include multiple embedded design parameters. Although the functional requirements should remain independent, having extra physical components and parts of a design contradicts a design with minimal information. This second axiom of design often makes physical integration of parts desirable as it reduces the information content of a design.

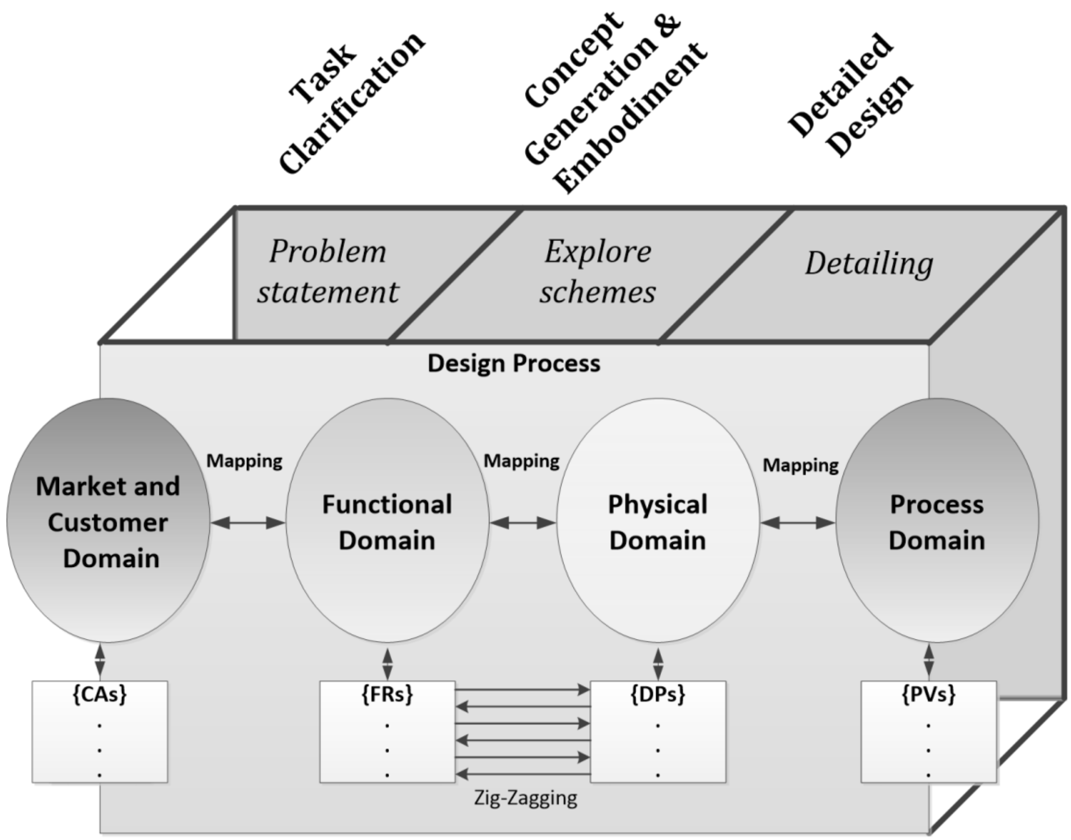


Figure 2.9 Axiomatic Domains of Design. This figure was adapted from Suh (1990) with permission. This depiction demonstrates the ongoing iterations that occurs between the four main domains of design as described in the literature. [14]

$$\underbrace{\overbrace{\begin{Bmatrix} \mathrm{FR}_1 \\ \vdots \\ \mathrm{FR}_i \end{Bmatrix}}^{\substack{\text{Functional} \\ \text{Domain}}}}_{\substack{\text{Functional} \\ \text{Requirements}}} = \underbrace{\overbrace{\begin{bmatrix} a_{11} & \cdots & a_{1j} \\ \vdots & \ddots & \vdots \\ a_{i1} & \cdots & a_{ij} = \dfrac{\partial \mathrm{FR}_i}{\partial \mathrm{DP}_j} \end{bmatrix}}^{\substack{\text{Mapping between} \\ \text{Domains}}}}_{\text{Design Matrix, } [A]=[a_{ij}]} \underbrace{\overbrace{\begin{Bmatrix} \mathrm{DP}_1 \\ \vdots \\ \mathrm{DP}_j \end{Bmatrix}}^{\substack{\text{Physical} \\ \text{Domain}}}}_{\substack{\text{Design} \\ \text{Parameters}}} \qquad (2.1)$$

---

[14] Equation (2.1) provides a formalized relationship between the domains; this equation relates the functional domain and the physical or artefact domain. The interactions in this matrix give rise to the theoretical design landscape discussed. Suh (1990) highlights that independence in design requires the design matrix to remain diagonal or triangular. In addition, the design remains linear in case where all elements a_{ij} are constant; however, commonly these elements represent functions of the design parameters and the design, making the design by definition non-linear. Further, elements a_{ij} and their interactions specify the range of system behaviors, such as those required by Ashby's Law of Requisite Variety to ensure the appropriate number of control states, given the number of possible variations in the design, necessary to maintain the effective response and performance of the system (Bar-Yam 2004).

Discontinuities between what the design-team needs to achieve functionally, specified in the vector of {FRs}, and how the design-team may achieve these goals in the physical domain, specified in the vector of {DPs}, motivates the focused exploration of the design landscape, leading to the eventual convergence on a design concept. Formally, the requirements provide a range of theoretical solutions, referred to as the system range. The conceptual design documented in the design matrix [A] similarly provides a range of possibilities for meeting these demands referred to as the design range. As the design matures the design range gradually merges with the system range, a common range emerges between the system range and the design range; this overlap helps to specify the probability of success in a design through a common range (CR). From a statistics perspective, the common range relates to the overlapping coefficient as a measure of agreement between the two distributions (Inman and Bradly 1989). Figure 2.10 demonstrates this concept as discussed by Suh (1990).

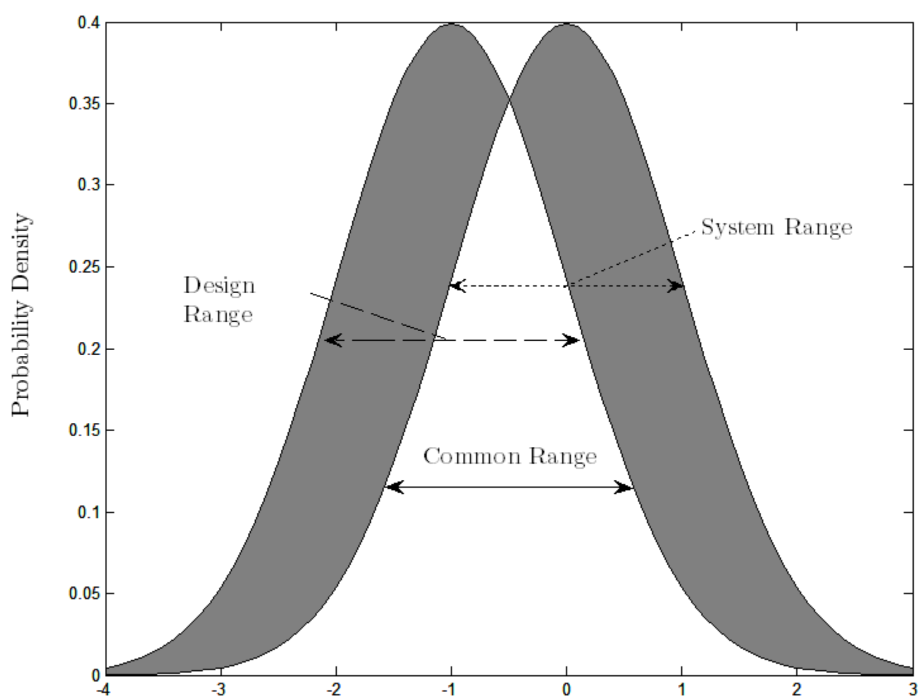


Figure 2.10 Ranges of Design. The figure provides a representation of the design ranges. These ranges relate to the probability that a design solution, given by the design range (DR), meets a set of functional requirements established by the system range (SR). The area of the common range (A_{CR}) under the joint probability distribution relates to the shared area of the design range and system range (i.e. $A_{DR} \cap A_{SR}$) provides the probability of design success. The distributions provided represent Gaussian functions for explanatory purposes; however, non-normal distributions remain viable alternatives.

Mathematically constructing the probability density function (pdf) for the common range follows from the generic relationship between the system range pdf and the design range pdf:

$$f_{CR} \ = \ min(f_{SR}(x,\mu,\sigma), f_{DR}(x,\mu,\sigma)) \qquad (2.2)$$

As Suh (1990) points out this relationship between the probability of achieving a functional requirement in the design range can be expressed in terms of both the functional requirements and design parameters:

$$P \ = \ \int_{DR^l}^{DR^u} p_s\,(FR)\,dFR \qquad (2.3)$$

Where:

$p_s(FR)$, the probability distribution function for Functional Requirements (FR)
DR^l, the lower bounds on the design range
DR^u, the upper bounds on the design range

The relationship provided by equation (2.3) allows Suh (1990) to describe the common range derived in equation (2.2) in terms of functional requirements:

$$A_{CR} = \ P \ = \ \int_{DR^l}^{DR^u} p_s\,(FR)\,dFR \qquad (2.4)$$

Finally, by tying together the second pillar of axiomatic design that defines the probability of success in terms of its inverse logarithmic relationship to information content, Suh (1990) provides the overall mathematical linkages necessary for understanding how information content limits the common range of design and diminishes its likelihood of success. This connection, shown in equation (2.5), allows for the connection between the common range, information content, functional requirements, design parameters, and the probability of success.

$$I = log_2\left(\frac{1}{A_{CR}}\right) = \ -log_2\,P = \ -log_2 \int_{DR^l}^{DR^u} p_s\,(FR)\,dFR \qquad (2.5)$$

These findings enable Suh (1990) to provide for an accounting of the overall probability of success for a design and for its information content. For uncoupled designs, since the probabilities remain independent, the information content simply represent a summation; however, for the coupled designs the problem represents a conditional probability. These relationships follow in equation (2.6) and equation (2.7) respectively.

$$I_{uncoupled\ design} = \sum_{i=1}^{n} I_i = -\sum_{i=1}^{n} log_2\ P_i \tag{2.6}$$

$$I_{coupled\ design} = -\sum_{i=1}^{n} log_2\ P_{i\,|\,\{j\}} \qquad \{j\} = \{1, \dots, i-1\} \tag{2.7}$$

These findings underscore some interesting facts regarding the design process and complexity. The equations show that increases in FRs do not necessarily decrease the likelihood for success of an engineering design. By adopting or modifying the previous definition of complexity to one that explicitly relates it to the likelihood of failure, an interesting result appears. Although, complexity represents something distinct from the complicatedness, *e.g.* the quantity of components, of a design, the relationships remain highly correlated. For the designer, this provides a general guidepost to minimize the number of opportunities for failure by limiting the information content and controlling the size. Sometimes minimizing these opportunities becomes difficult when balancing the demands of continuous product development initiatives. For the designer, the key to this balance rests in improving products incrementally such that resolution into the design range is preserved. The conceptual design-team should spend considerable effort in the refinement of a design concept that reduces its information content to a minimum, which conversely for the designer means maximizing the common range of a design (CR) to limit all discrepancies between the requirements and the functioning of a design. These results highlight the necessity to explore design alternatives carefully, which can often pose a challenge to new designers. Design fixation can set-in, making feasible solutions act as strong attractors for the design-team. Without a proper survey of the design landscape, these attractors can lead the design-team to a premature convergence on a feasible, but suboptimal solution (i.e. local maxima). This can lead to allocative inefficiencies of resources for a design effort, and, in a highly competitive space, can mean the failure of a product launch and opportunity costs.

For the design of complex engineered systems, the axiomatic design framework provides insight into the interplay between design domains. However, this framework neglects an accounting of the countless interactions between both the design-team and the relevant stakeholders. Often convergence on a solution in design resembles an 'emergent' phenomenon from complex systems (i.e. patterns arising from a multiplicity of relatively simple interactions). More specifically, we consider information content (i.e. entropy) and uncertainty in our C^2D approach as arising from the number of design elements N and the degree of interdependencies K between these elements as discussed further in Chapter 3 (cf. 3.2.2) and after Kauffman (1990) discussed later in Section 2.3.2. The axiomatic framework provides a structure for the development of our design landscape, while we look towards other system design frameworks to provide a holistic understanding of the DAU. Socio-technical systems design provides one of these frameworks.

2.1.3 Design as a Socio-Technical Discipline

Socio-technical systems design (STSD) strives to integrate the confluence of human, social, organizational, and technical factors relevant in the design of systems into a holistic framework. The socio-technical concepts inherent in this framework focus on the need to account for both social and technical factors in design. Although STSD techniques aim to ensure that both technical and social aspects of a system receive simultaneous joint consideration, disconnects between these methods and those employed in traditional technical engineering continue to limits its widespread adoption (Baxter and Sommerville 2011). Further, Eason (2001) found only a few user-centric approaches, such as STSD, in use. This failure of the design community to adopt more holistic design perspectives continues to result in systems that may meet technical requirements but fail to deliver the expected level of functionality and value to a user. As discussed in the introduction, failures commonly arise out of a predominately techno-centric approach to design; these techno-centric approaches are prone to these failures, in part, as they do not capture the complex relationships within the organization, the designers engaged in the design process, and the system that supports these processes (Norman 1993; Goguen 1999). In order to capture these complex processes and provide a holistic and methodical framework, Baxter and Sommerville (2011) proposes the extension of the STSD approach to the creation of a *socio-technical systems engineering* (STSE) field. This proposed STSE field spans the complete systems engineering processes currently used, to include procurement and acquisition, specification, design, testing, evaluation, operation, disposal, and the evolution of complex systems. The emergence of this field draws on multiple research communities and perspectives, including complex adaptive systems thinking. Table 2.1 highlights the interesting cross-disciplinary relationships in the literature.

Table 2.1 Relevant Literature Relating Complex Adaptive System, Socio-Technical Systems, and Systems Engineering. Intersecting perspectives of design and their relative strength, from implied (†) to explicit literature focus (†††). This measures strengths relative treatment of design as a socio-technical system (STS), a complex adaptive system (CAS), or a traditional systems engineering process (SE). These intersecting research domains represent essential components of the emerging foundations of socio-technical systems design (STSD) and traditional systems engineering (STSE).

	STS	CAS	SE
Principles of Socio-technical Design (Cherns 1976, 1987)	†††		†
Soft systems methodology (Checkland 1981)	††	†	††
Designing human systems, ETHICS method (Mumford 1983)	††	†	†
Principles of design (Suh 1990)			††
Cognitive systems engineering (Rasmussen et al. 1994)	†		†
Scandinavian system development (Bjerknes and Brattereig 1995)	†		†
Effective systems design (Mumford 1995)	††	†	
Designing simple organizations, complex jobs (De Sitter et al. 1997)	†	†	
Contextual design (Beyer and Holtzblatt 1999)	†		††
Strategy as design: a fitness landscape framework (Maguire 1999)	†	†	
Cognitive work analysis (Vicente 1999)	††		†
Design rules and modularity (Baldwin and Clark 2000)		†	†
Sociotechnical principles for system design (Clegg 2000)	††		†
Technology, a complex adaptive system (Fleming and Sorenson 2000)	†	†††	
Design rules and modularity (Baldwin and Clark 2000)		†	†
Socio-technical approach to systems design (Mumford 2000)	†††		†
Socio-technical design of work systems (Waterson et al. 2002)	†††		††
Ethnographic workplace analysis (Martin and Sommerville 2004)	††		†
Complexity: theory and applications (Suh 2005)	†	†	†††
Cognitive systems engineering (Hollnagel and Woods 2005)	††	†	†††
Information exchange in design (Maier et al. 2006)		†††	
Socio-technical systems, design (Baxter and Sommerville 2011)	†††		††
Adaptive socio-technical systems design (Dalpiaz et al. 2013)	††	†	†

The basis of socio-technical design arises from general systems theory (Bertalanffy 1968). From a STSD and STSE perspective, the interactions that occur between people, technology, and the environment drive the process of design by enabling the designer to understand the design objective and search the design landscape; these designer interactions span the multiple phases or domains of design as discussed, with each have phase and domain having varying attributes. Sociologists view these systems as social systems, psychologists view them as cognitive systems, and engineers view these systems as information and hardware systems; however, STSD and STSE examine each of these perspectives in order to explore the common truths across the disciplines, *i.e.* the structural similarities and isomorphisms across the various perspectives of design (Bertalanffy 1968). Consequently, this approach does not neglect the basic principles of design; it instead strives to understand the system from its totality of interactions and feedback between the hardware and software components and the organization, user, stakeholders, and wider environment. Basic STSD principles originally organized themselves around ten guidelines from Cherns (1987), which correlate to both fundamental design axioms as well as good design-team-design principles. These principles include:

1. Compatibility:
    - the process of design should match the design objectives, *e.g.* it should promote participative design (i.e. co-design, cooperative design)
2. Minimal critical specification:
    - the means to achieving objectives should not be overly constrained or specified
3. Variance control:
    - variances in a design behavior should be controlled at the source
4. Boundary control:
    - boundaries should not impede the sharing of information, knowledge, or learning
5. Information flow:
    - information should be provided to those who need it, when needed
6. Power and authority:
    - those who need access to resources to carry out their responsibilities should have access to them and authority to control them
7. Multifunctional principle:
    - individuals and teams should take on multiple roles to increase their response repertoires
8. Support congruence:
    - supporting systems and subsystems should match the design tasks, *e.g.* planning and technical tools

9. Transitional organization:
    - transitions represent socio-technical design challenges themselves; they require planning and design, and can result in deviations from the old system
10. Incompletion:
    - redesign is continuous and the function of self-regulating teams

These overarching guidelines have themselves gone under considerable change and rethinking. Baxter and Somerville (2011) provide a highlight of these changes, including extensions to the principles laid out in Chern (1987) by Clegg (2000). These extensions provide a currently accepted set of 19 socio-technical principles for system design organized into three high level categories (i.e. meta-principles, content principles, and process principles). These principles include:

- Meta principles for Socio-Technical System Design
    1. Design is systemic
    2. Values and mindsets are central to design
    3. Design involves making choices (i.e. decision making)
    4. Design should reflect the need of the stakeholders
    5. Design is an extended social process
    6. Design is socially shaped
    7. Design is contingent
- Content principles for Socio-Technical System Design
    8. Integration of core processes internal to the design effort
    9. Design entails multiple task allocations between humans and machine
    10. System components should be congruent
    11. Systems should be simple in design and make problems visible
    12. Problems should be controlled at the source
    13. Means of undertaking tasks should be flexibly specified
- Process Principles for Socio-Technical System Design
    14. Design practices is itself a socio-technical system
    15. Systems (and their designs) should be owned by their managers and users
    16. Evaluation is an essential aspect of design
    17. Design involves multidisciplinary education
    18. Resources and support are required for design
    19. System design involves political processes

Early on in the design process, the STSD and STSE focuses on the goal of providing a more acceptable system to the end-user and delivering improved value to the stakeholders of the system. The principles from Chern (1987) and Clegg (2000) expand on the fundamental axiomatic rules and general models of design, to provide a view of design as a social process focused around the end-user. As the design process matures, STSD and STSE evolves to match the needs of the current design phase (Maier, Troy, Johnston, Bobba, and Summers 2006). As seen in the axiomatic design approach, transforming user needs into functional requirements and these requirements into design parameters requires intense interactions between designers and a high degree of creativity; additionally, the *socio-technical* views of design highly stress the need to extend the collaboration between the user and designer further into design. Although, STSD and STSE promotes this model of continued participatory design, there remains a lack of normative understanding of how to accomplish this; typically, the difficulty stems in the selection of participants and, more so, in the determination of the necessary levels of skills and experiences for the participants in the process. This lack of understanding leaves it difficult to apply the STSD methodology routinely (Damodran 1996; Scacchi 2004; Baxter and Sommerville 2011). Nevertheless, the continued inclusion of the user in the design process, across design approaches, shows promise at minimizing discrepancies between user expectations, and the resulting design artefacts and their performance.

One approach for minimizing this discrepancy is to create a nurturing and organic environment for collaboration between the designer and user, a common characteristic to managing complex adaptive systems (CAS). Interestingly, the characteristics of the open socio-technical system perspective mirrors many of the same defining attributes of a CAS, as addressed later in the chapter. The original term *socio-technical systems* from Emery and Trist (1960) described systems that involved "a complex interaction between humans, machines, and the environmental aspects of the work system." As discussed, designers face an increasing degree of these complex interactions between technical and social aspects of their work systems. Today the use of the term *socio-technical systems* applies to almost all complex systems, including the more specific CAS. Table 2.2 highlights these links by comparing the Badham, Clegg, and Wall (2000) five essential necessary characteristics of socio-technical systems in general to those of CAS. As seen in this summary comparison, the fact that design clearly represents a socio-technical system creates the inference that it may also be a CAS. The research builds on this notion and includes, as shown subsequently, incorporates this fundamental inference as a building a block in the creation of a model of design-teams.

Table 2.2 Comparison of Common Characteristics between Open Socio-Technical Systems and Complex Adaptive Systems. As described by Badham et al. (2000), this comparison provides the initial foray into the larger question of whether design and more specifically the Designer-Artefact-User system represents a complex adaptive system in addition to being a socio-technical system, *i.e.* a complex adaptive socio-technological system.

	Socio-technical	CAS
• Systems consists of interdependent parts	✓	✓
• Systems adapt to pursue goals in external environments	✓	✓
• Systems have equifinality (i.e. multiple pathways to achieve system goals, implying the presence of decision-making)	✓	✓
• Systems have an internal environment having separate but interdependent technical and social subsystems	✓	✓
• System performance relies on the joint optimization of the technical and social subsystems	✓	✓

In the C^2D approach presented in this research, designers (i.e. agents) individually represent the decision-makers for the design process. For the STSD and STSE approaches, understanding how these interactions form remains an essential research building block. Most research foregoes the analysis of these dynamics due to their difficulty to model and capture. The C^2D approach allows modelling of these design agents as they work together to create networks of collaboration that inspire, support, and evaluate their work, *i.e.* creating a design-team and design network. Many of the key determinants for success in these efforts arise from the very nature of how the interactions between designers form and disperse; we refer to this conceptual area of examination as the dynamics of team-formation. These dynamics play an ever-larger role in the nature of design given the demand for large multi-disciplinary and diverse teams to overcome the growing complexity seen in design.

2.1.4 Changing Nature of the Designer

This process of design and, more specifically, the processes of transforming ideas into solutions appears more relevant today than it has ever in the past. With the growing complexity of user and social demands driving an increasingly difficult design process, design, which once was the purview of a few engineers, has now become the domain of growing teams of engineers and specialists. Mitigating this complexity, however, underscores a schism as to what makes a designer. As touched upon previously, there exists two fundamental perspectives on design. One perspective considers the designer as technician with deeply planted roots in the engineering sciences, including analysis, modelling, and computation, and, the other perspective places the designer as an artisan deeply rooted in experience and creativity (Griffin 2007; Lamb 2008). Beder (2008) points out that although engineering design once was the purview of artist, the move away from engineering design as an art or craft resulted in part from a conscious effort of engineering schools to differentiate themselves from less socially appealing forms of vocational training. With radically advancing scientific methods and analytical techniques, this balance of perspectives has continued to accelerate towards the scientifically based designer. However, the question arises, is the analytically focused skill set adequate to confront the current challenges of design? Figure 2.1 summarizes research from Dong (1999) that shows that each of these camps offer their own unique benefit depending on the complexity of the system; however, interestingly, as seen, the complexity of systems benefits the most from an experience-based model of design understanding, which incidentally relies on teams.

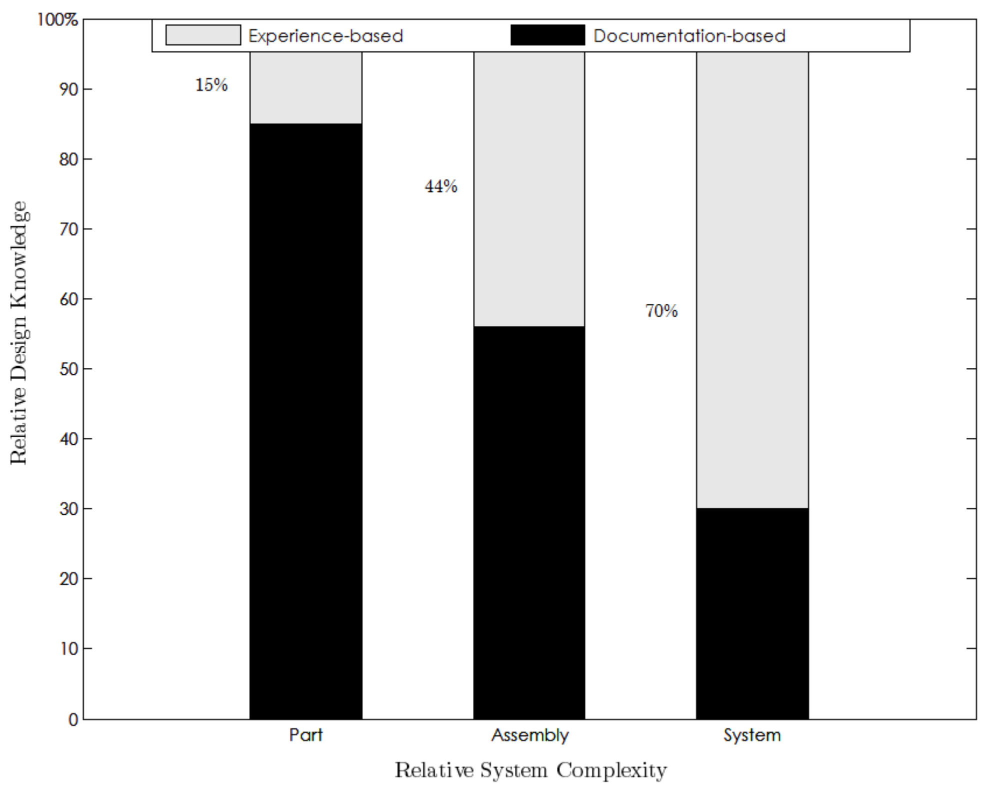


Figure 2.11 Relationship of Relative System Complexity to Relative Design Knowledge. This figure from Dong (1999) demonstrates that increasingly complex design tasks requires teams of increasingly experienced designers.

2.2 Complex Adaptive Systems Thinking and Design

The literature unambiguously provides strongly support for representing design as a complex socio-technical process comprising multiple interacting socio-technical elements and stakeholders. This perspective lead to the inevitable question as to the nature of this design process, *i.e.* what kind of complex socio-technical process is design? In fact, the literature suggests design and its various interactions between stakeholders, technology, and designers form the basis of a particular type of system, a complex adaptive system (CAS). In short, perpetual novelty, *i.e.* a high degree of adaptive capacity, characterizes the essential essence of these systems. In human systems, creativity often underpins this capacity for adaptation. As discussed in the introduction, even the most rudimentary social systems demonstrate what Holland (1999) refers to as "perpetual novelty," an outcome arising from the high degree of interactions among a set of autonomous agents (e.g. design-team members). Perpetual novelty assures that new patterns of behaviors continually emerge, even in rudimentary examples like chess. This concept of perpetual novelty remains especially evident in the process of engineering design, where design-teams, each composed of multiple agents, routinely navigate an immensely complex space of design possibilities. This complex space defined by the design landscape emerges from the interplay between the theoretical technology possibility space and the specified design approach and provides a state space that describes these possible design configurations. The process of creating endless design variety and product improvements underscores the theoretical linkage between perpetual novelty and design as a complex adaptive social-technical system (CASS).

Managing engineering design as a holistic system, and in particular as a CASS, requires both new models and paradigms that reflect modern systems and system of systems thinking. Miller and Page (2007) point out that in an attempt to deal with the inherent complexities of human systems, such as design, most current management approaches must employ numerous assumptions. As discussed in the literature, these assumptions even when artfully constructed degrade the traceability between the management system and the essential nature (e.g. processes) of the CASS. These disconnects result in models that do not fully capture the intuitive behaviors guiding system interactions. These existing models, including current mechanical equilibrial models and organismic homeostasis models from organizational and sociological theory, lack the feedback aspects and the adaptive elements that drive complex adaptive socio-technical systems (Buckley

1967; Gharajedaghi 1999; Buckley, Schwandt, and Goldstein 2008). The requisite simplifying assumptions in these models often lead to the same results as many rational decomposition models, they do not adequately capture emerging patterns of behaviors. Understanding these patterns of beneficial interactions could allow for improvement to the design process through the design of management strategies. To understand these emergent characteristic we establish design in the context of a CAS to address these factors, such as emergence, self-organization, and path dependency. We build on this perspective by including the social (i.e. the designer) and technical (i.e. design landscape) elements to arrive at a CASS perspective of design.

2.2.1 Defining Design as a CASS

Presenting design in the context of the modern systems perspective departs from many of the existing traditional frameworks and represents design foremost as a social system. Buckley (1967) proposed that social systems in general represents a form of complex adaptive systems (CAS), a type of system characteristically comprising multiple interrelated and interdependent elements that learn, adjust, and adapt to their environment. This characterization applies well conceptually to the aspects of design. The original CAS frameworks proposed the analysis of systems through the prism of information exchange. Buckley (1967) proposed examining systems using the underlying dynamics surrounding the exchange of information, as opposed to energy transmission used in most traditional models, between a set of linked elements in the system or organization. In this framework, outcomes in an organization emerge from a network of interactions among individuals. These complex networked systems are open and negentropic (tending to ordered and emergent behaviors).

Since this original conceptualization of CAS, several views of CAS and complex adaptive system of systems (CASoS) have emerged. Holland (1999) provides one of the most commonly cited views of CAS, describing these systems as dynamic networks of many interconnected “agents” (e.g. system/organizational elements, decision-makers) interacting constantly with their environment (e.g. political/organizational, economic, operational, technical), themselves, and other agents. In this framework, the very large number of simple decisions made every moment by many individual agents drives the behaviors of CAS. The collaborative process of design entails many of these characteristics. In the context of design, individual design agents follow simple rules to improve the value of their interest (e.g. balance of performance and cost) while the collective system explores a technology possibility set. This exploration for design occurs under varying degrees of coordination, usually controlled through a systems engineering and integration element. For instance, in open source projects design typically entails a highly fluid and organic process, whereas complex aerospace design projects typically represent more structured internal rules for the individual design agents (e.g. maximize performance). However, in both extremes the resulting interactions and design system represents an exemplar of an immensely complex adaptive socio-technical system and endeavor. As this research explicitly treats these agents as social units, *e.g.* designers, interacting with technology we consider design as CASS. Similar research from the Santa Fe institute to understand the complexity of the natural, cultural, and social world, especially as applied to network dynamics and robustness, exemplify the potential benefits of exploring the DAU in this wider context of a CASS (Dillon 2013).

The literature strongly supports treating design as a complex adaptive system. Maier, Troy, Johnston, Bobba, and Summers (2006) illustrate this connection by comparing the Designer-Artifact-User (DAU) system and its behaviors to the indicators of CAS behaviors proposed by Gell-Mann (1994). To do so the comparison examines the information exchanges within the DAU, which occur between the design-team and technical artifact, the design-team and the user, and the user and technical artifact. As seen in the earlier discussion of axiomatic design, the relative degree of information exchange within the DAU adapts to match the current phase of the design. The general DAU system, when viewed as a CAS, must also contends with several externalities (e.g. economy, regulations) that govern its behavior. Figure 2.12 provides a depiction of the DAU and its influences. Maier et al. (2006) found that the resulting behaviors exhibited by a general DAU system during each of its design phases mirrors the characteristic cyclic behaviors inherent to a CAS. Gell-Mann (1994) provides these characteristic phases of CAS as: 1) coarse graining of information from the real world, 2) identification of perceived regularities, 3) compression into a schema, 4) variation of schemata, 5) use of a schemata, and 6) consequences in the real world exerting selection pressure that affect the competition among schemata.

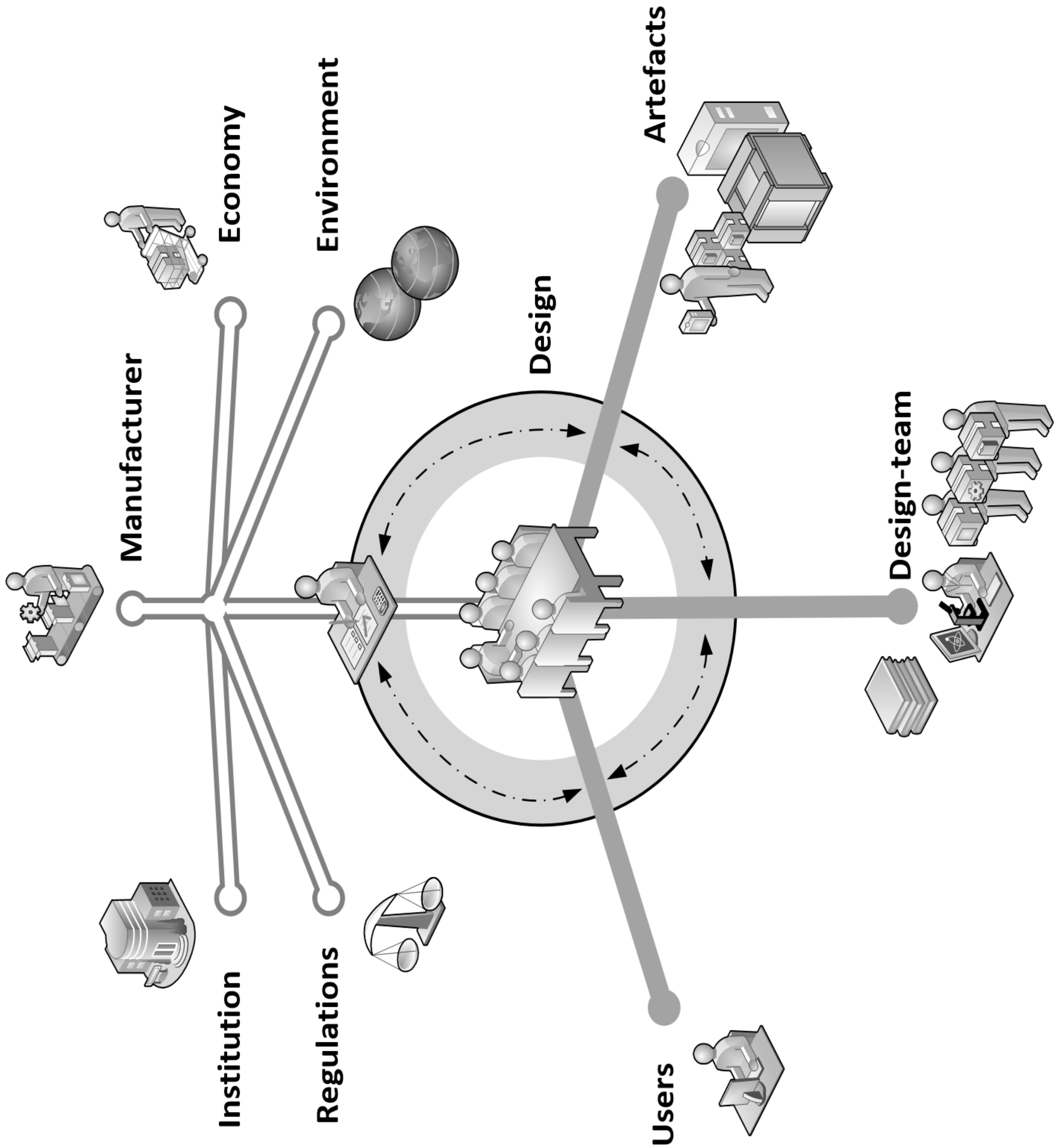


Figure 2.12 Designer-Artifact-User System. This figure describes the complex adaptive socio-technical system, the DAU adapted from a discussion of the DAU concept by Maier et al. (2006).

This research predominately focuses on the behaviors of design-teams exploring the design landscape as these corresponding phases represent the largest advantage points concerning schedule and cost for the overall design process. Among these corresponding CAS phases, this most corresponds to the identification of perceived regularities and establishment of requirements, the mapping of a technical artifact or engineered-system outcome during the compression of a schema, and the final refinement of the conceptual design during the variation of the schemata. Relating these phase characteristics of CAS to this general design process follows from Maier et al. (2006):

1. **Coarse graining of information from the real world**

   During the problem definition phase, the design-team works to understand the design problem. This phase requires a period of coarse graining, where the design-team gathers information about the design problem from all available sources in the real world. This process begins to establish the boundaries of the design space based on the design problem, commonly in the form of an initial set of user and customer requirements. This process of gathering information in design represents the coarse graining of information process seen in CAS.

2. **Identification of perceived regularities**

   As the design transitions from its initial work specifying the design problem and after agreeing on the design objectives, the design process moves to an ideation phase. During this phase, the design-team works to refine their understanding of the design problem further, typically with refined functional requirements. This requires the design-team to sort out the data gathered during the earlier coarse graining phase. Additionally, designers in this phase ferret out the technology possibility space for possible design approaches. After establishing an initial design approach and structure, the boundaries of the design space give form to the design landscape. Varying design configurations correspond to points on this landscape and, based on its location on the landscape, to fitness values. These fitness values describe how well a design meets the technical needs and expectations of the user.

3. **Compression into a schema**

   After sufficiently forming a feasible design space (i.e. the design-team sufficiently understands the design problem and available technologies), the search on the design landscape must continually focus in order to arrive at an acceptable conceptual design. The conceptual design phase for a DAU system results in the eventual compression of a design concept into a schema, *e.g.* the embodiment of a design. This compression into a schema involves the exploration of the design space using ideation and evaluation techniques and, ultimately, the focused selection on a feasible concept for development and embodiment. The resulting schema represents an explored conceptual solution. This phase relies on the large collaborative process between designers where a core team constantly explores the feasible design space, and its encapsulating design landscape. The collaborative process between the designers propels the search for a workable design schema through convergence. After converging on a general schema, divergence within the team occurs that allows the design-team to explore variations that may improve upon the schema.

4. Variation of a schemata

After the design-team finds an initial system concept or schema, the design-team must continually improve, test, and refine the conceptual design in order to arrive at a production ready design. This can often mean that the design-team must iterate extensively between the earlier phases of the design space. In other cases, such as for product improvement, the entire design process may start at this point. These cases focus only on the modification of an existing system to meet new requirements, *i.e.* variant design. However, these processes still include an ongoing process of iteration from its engineering baseline. These iterative processes of a DAU system exhibit the same characteristics seen in the variation of a schemata phase of CAS cycles. CAS systems similarly undergo a process of continual adaptation (Maier et al. 2006). In the context of the landscape, this may manifest as a member of the design-team exploring an increasingly localized neighborhood (i.e. proximal points) for continued improvements to design fitness.

5. Use of a schemata

The use of a selected schema for a DAU system occurs with the production of a finished engineered system (i.e. artefact) delivered to the user, often through the marketplace (Maier et al. 2006). The use of the schemata extends beyond the design-team to include the end users, manufacturers, maintenance and service personnel, and stakeholders of the system, to include society. This use or execution of the schemata represents a consistent analogue to the use of schemata in CAS (Gell-Mann 1994).

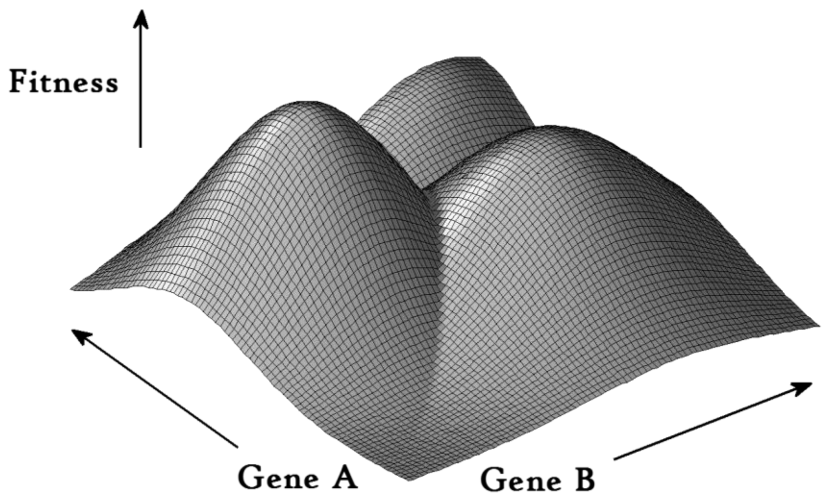
6. **Consequence in the real world**

   Selection pressures from the outside environment influence a DAU system as they do in CAS systems. These pressures for a DAU stem from multiple sources (e.g. changes in the economy, changing user preferences, regulatory changes) and provide feedback pathways. This means that the DAU systems often face dynamic conditions that affect the decisions of the designer. Implicit to these conditions is the concept of a dynamic design landscape, with variations in the landscape based on these external selection pressures altering the structural design approach of the design-team.

The comparison of the phases of the design cycle to the phase of complex adaptive systems supports representing the DAU system as a CAS. By specifically including the socio-technical factors, *i.e.* the design-team formation dynamics and the structural design complexity, we augment this CAS understanding and provide a wider perspective of the DAU as a complex adaptive socio-technical system (CASS). In short, at its most fundamental level the socio-technical interactions within and between the design-team, the designer, the users, the artefact, and the design environment gives rise to the notion of a DAU system as a CASS. We use these notions in the implementation of the DAU and its decision making-processes as a CAS in the C^2D model and Chapter 3 (Section 3.3.3).

2.3 Fitness Landscapes for Complex Problem Spaces

The concept of a *fitness landscape* traces its origin to the very early theory of evolution and natural selection, with its first explicit mention from the field of theoretical evolutionary biology in the early 1930s by Wright (1932). In the context of biology, fitness generally measures the ability of an organism to produce offspring. In this traditional definition, fitness defines the relative reproductive success of an organism in passing its genes to the next generation. In its most common usage, fitness provides a measure for the likelihood that the combined inherited characteristics produce utility in offspring (Holland 1995). Since their initial applications, fitness landscapes have proved valuable analogies in other fields, to include modeling entropic systems and combinatorial optimization problems in organizational change (Levinthal 1997). We equate these fitness landscapes to represent value-functions for the case of design and compare them more broadly to production functions (as seen in Figure 2.13).



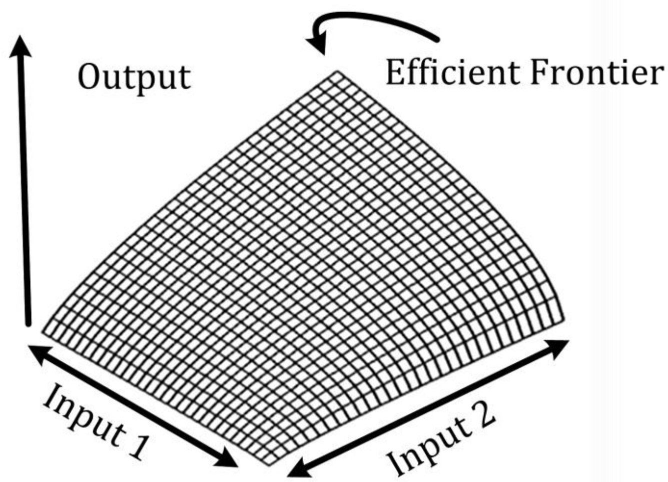


Figure 2.13 Example of Fitness and Productive Landscapes. This figure compares a rugged fitness landscape (top) to the performance landscape of a traditional Cobb-Douglas Function (bottom). The rugged fitness landscape maps the interactions between genes and the impact of these interactions on the overall fitness of a species in a traditional application. However, we can apply this rugged landscape to represent the complexity of a design approach. We also can equate these fitness landscapes to those of traditional econometric performance and production functions such as Cobb-Douglas production functions (cf. Section 2.5.1). In the case of econometric and performance theory, landscapes characteristics typically arise from their adherence to strict rules and axioms of production, including convexity restraints that result in their smooth surfaces. By relaxing the production axioms, we subsequently demonstrate the equivalency between these productive landscapes (such as the one on the bottom) and performance landscapes (such as the one described above).

Fitness landscapes have multiple varieties depending on their application. The visualization of complex spaces with peaks and valleys provided by the fitness landscape make it a desirable analogy to multiple problem sets concerning adaptation and optimization, including in the depiction of a design possibility space at the center of this research. In these depictions, the peaks of landscapes generally represent solutions. In this construct, the highest peak of a landscape correspondingly represents the best solution (i.e. the global optimum). Essentially, these *fitness landscape* models offer a geometric description of an optimization (e.g. adaptation) problem. Mathematically, this landscape is a triplet (S, ν, f), such that (Merz and Freisleben 1999):

- S defines the search space (i.e. set of admissible solutions);
- $\nu: S \to 2^{|s|}$ defines a neighborhood function; and,
- $f : S \to \mathbb{R}$ is the fitness function that associates a real-valued fitness value to each solution

This mapping and enumeration process from the neighborhood function ensures that each $s \in S$ includes a set of neighbor solutions $\nu(s) \subset S$. Similarly, the fitness function provides the optimizing function for the search space. These fitness values provide the resulting heights of the landscape.

2.3.1 FITNESS LANDSCAPES: ORIGINS IN BIOLOGY

Use of fitness landscapes provides a methodology to describe the dynamics of evolutionary optimization and a means to visualize the underlying relationships between genotypes and the probability of reproductive success. The natural selection process is evident in the movement or the adaptation of an agent as it continually moves uphill in search of improved fitness. Fitness landscapes provide the ability to visualize the impact of interactions between different genes and the resulting fitness, in essence providing a potential performance landscape for this natural selection process. The most common types of fitness landscapes include the genotype (i.e. genetic constitution of an organism) to fitness landscapes described originally by Wright and, its derivative, the phenotype (i.e. the set of observable characteristics of an organism) to fitness landscapes.

Originally, Wright (1930) introduced the concept of fitness landscapes to explain and visualize the relationships between genotypes or phenotypes and the probability of reproductive success; the construction of these frameworks and their variations have since greatly improved the theoretical understanding of how imperfections arise in evolutionary processes. Figure 2.14 demonstrates this concept using a contour map and a two-dimensional landscape, similar to the original figure introduced by Wright (1930). In this example landscape, it is clear that there exists multiple attractors, *i.e.* competing solutions represented by peaks denoted with 'plus' signs, surrounded by valleys denoted with 'minus' signs. These competing solutions are attracting sets, $\{A\}$, which is a closed subset of the phase space such that multiple choices of the initial conditions evolve the system towards these subsets. More formally, these competing solutions form a neighborhood of attractors or a basin of attraction, denoted as $B(A)$, such that all points b, with $time \rightarrow \infty$, enter $\{A\}$. Movement on this theoretical space towards these attractors gradually moves the population of an entire biological population uphill; this movement represents the adaptation of a biological entity as it searches out higher fitness. Depending on the features of the landscape, an adaptive walk may also lead to local optima (i.e. points from which no paths lead to a higher value) that represent suboptimal solutions.

Originally, Wright (1931) related a continuous a dimension of genotypes to fitness via a hypercube, where the connections between genotypes represent mutational pathways that give rise to the fitness (i.e. fecundity) of a biological entity. Figure 2.15 reproduces this hypercube approach to fitness landscapes. The increased interconnectedness (i.e. degree of interactions and interdependencies) similarly gives rise to the ruggedness of this landscape; biologically this ruggedness equates conceptually to epistasis, a phenomenon in genetics where the expression of one gene depends on the presence of one or more 'modifier genes'. Because of the presence of this modifier gene or genes, when a phenotype becomes expressed the field of genetics labels this effect as an epistatic relationship, while, conversely, the suppression of a phenotype in the field of genetics represents a hypostatic relationship (Lush 1935). Germane to this research is the concept that these interactions between genes and 'modifier genes' often result in complex and nonconvex relationships, contrary to typical econometric approaches. In C^2D, we consider the equivalent of genes in design as requirements, and modifier genes as those requirements that influence the functioning on another requirement (a definition that remains consistent with the analogy of genes and modifier genes). These landscapes allow us in the case of C^2D to similarly describe the relationships between design requirements and their design parameters, or more generally in the case of any production system, the inputs, outputs, and relative performance or fitness of a system.

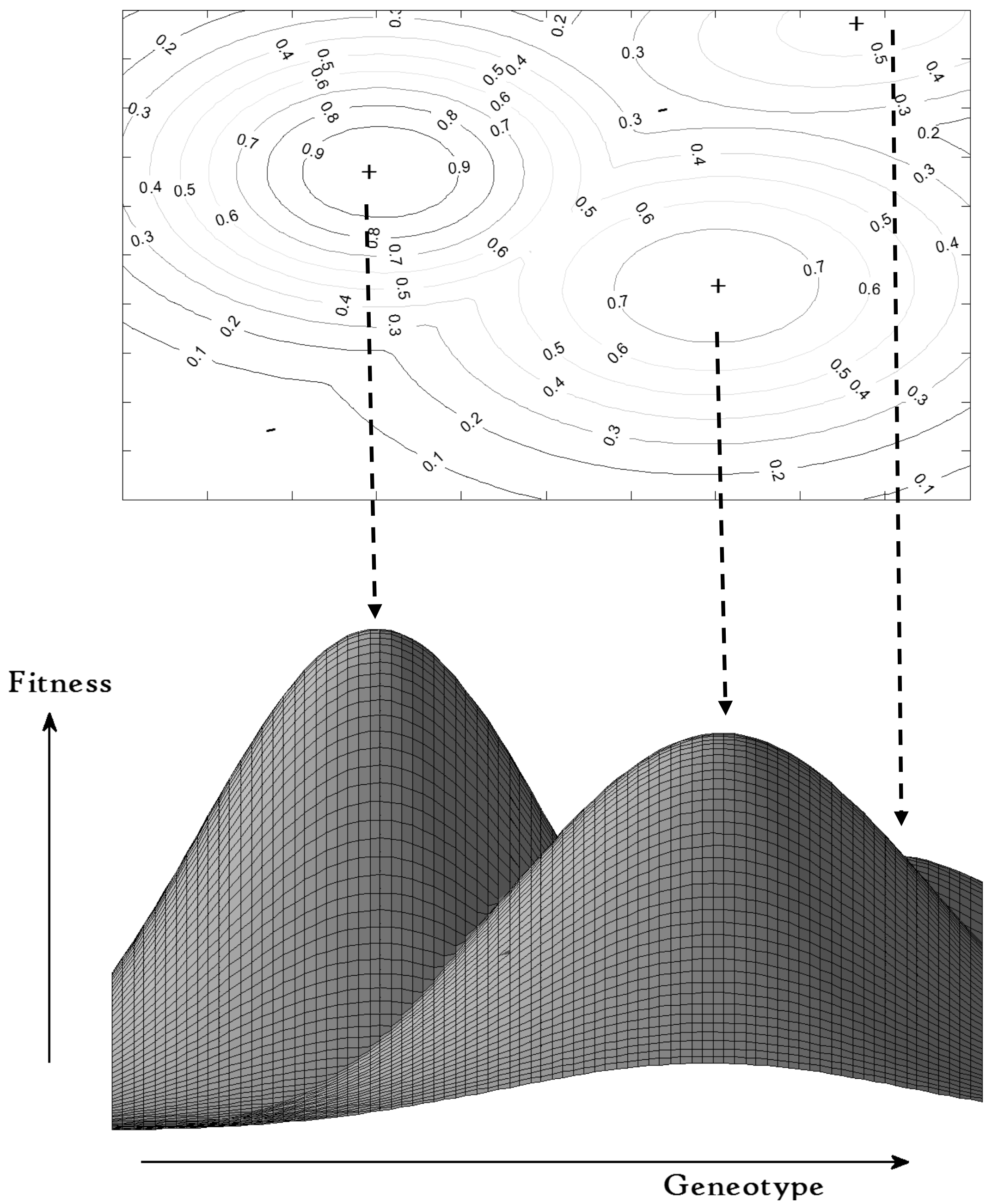


Figure 2.14 Representation of Fitness Landscapes Using Contour Maps and a Two-Dimensional Plot of Fitness Values to Genotypes. This is a reproduction of the concept originally posed by Wright (1931) relating a network of genotypes and their interactions to fitness. In this original conceptualization, genotype space extends to multiple dimensions in the form of a hypercube. The contour lines in this representation correspond to relative fitness or adaption. The above utilize a Gaussian landscape generator, discussed in the coming section, to generate the landscape and associated contour plot. The greatest limitation for this 3D landscape visualization is that it reduces higher dimensionality, which ignores the resulting hyper-volume areas that would otherwise generate holes and curves in the landscape. This could lead to loss of information (Kaplan 2008). The following figure show the hyperspace depiction of this genotype space (Wright 1932).

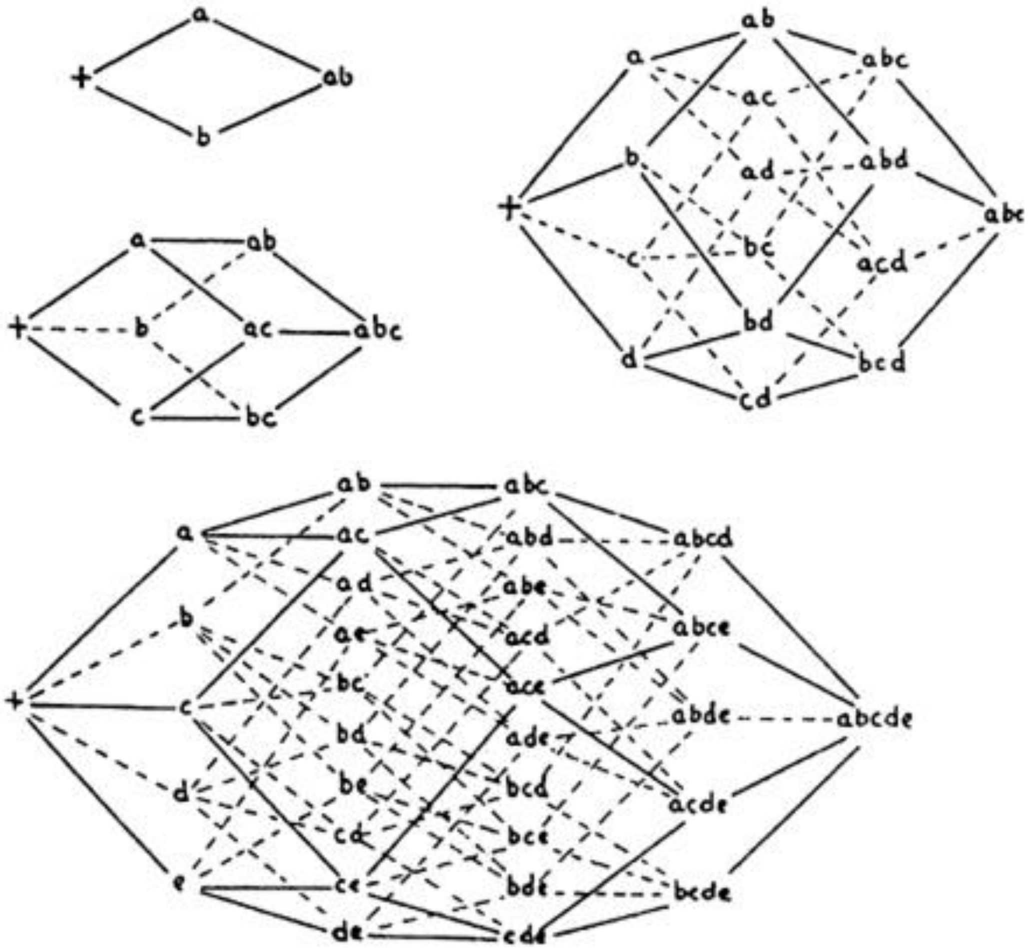


Figure 2.15 Wright (1932) Representation of Fitness Landscapes Using a Hypercube. Representation reproduced from Wright (1932) with permission to show combinations of two to five paired alleles giving rise to a fitness landscape. This figure shows that an increase in alleles, at one or more loci quickly creates a complex and hard to manage model from a dimensionality perspective. Nevertheless, this landscape provides a strong conceptual basis for addressing the question of how do mutations, usually deleterious for an organism, lead to greater fitness for a species population. As Wright (1932) argues, most combinations of alleles represent valleys on a fitness landscape (also commonly referred to as an evolutionary or adaptive landscape); in fact, a population would only find a small percentage of the overall landscape acceptable. This is similar to design, where only a few combination of design parameters and functional requirements provide valid designs. Wright (1932) notes that for an organism with two loci and two alleles each, there are four possible genotypes, each of which remain only one-step (roughly one mutation) away from two genotypes and two moves away from another. Similarly, for three loci with two alleles each there are eight possible genotypes, each of which remains only one-step away from three genotypes, two steps away from three genotypes, and three steps away from one genotype. It is through this perspective that these steps represent mutagenic pathways for an organism. Interesting, the total number of steps equals to N genotypes minus one. Additionally, the number of nodes in this diagram equates to the number of alleles, usually two, raised to the power of A loci, *i.e.* equation to 2^A; these relationships, as seen later, allow for dimensionality reduction through the adoption of a related approach and model, the NK landscape from Kauffman (1971).

Today these representations help computational biologist predict the relationships between evolutionary mechanics and the fitness of a biological organism. These explorations include understanding how phenotypic expressions occur from a bacteria or virus depending on epistatic interactions, this includes understanding the evolution of E. coli bacteria and the HIV-1 virus as well as the potential emergence and trajectories of drug resistance (cf. Appendix D for further discussion on current applications of fitness landscapes). Even the simplest of biological entities, such as the free-living transparent nematode (*Caenorhabditis elegans*) or common yeast (*Saccharomyces cerevisia),* have immense complexity when examining the underlying genetic regulations and requires complex bioinformatics based computation analysis (Haldane, Manhart, and Morozov). Unlike many physics based representations where minimal energy represents basins of attractions, local optima form peaks in biological fitness landscape and act as attractors. As with any complex system, considerations regarding attractors and their basin structures are important to the final-state predictability of a system. The resulting effect of these attractors on evolutionary processes mirrors a gradual form of the hill-climbing optimization process where agents search their neighboring feasible regions for improvements (i.e. fitness), in this case searching for an improved design fitness where a higher fitness value implies an improved solution. Convergence of agents around local optima can cause the search for fitness to cease prematurely. In some cases, the convergence occurs on multiple peaks, which can lead to an event known as allopatric speciation. In this event, an original population becomes vicariant (i.e. isolated from each other) and may even possibly evolve into two different species (Mayr 1970). In the context of teams, this represents the formation of possible splinter groups. Wright (1930) demonstrated that stochastic fluctuations in small populations, including these divided subpopulations, could also lead to an overall higher fitness.

A relatively simple and relevant fitness landscape for design applications stems from traditional biological genotype and phenotype mappings to fitness. A phenotype is the set of observable characteristics (e.g. eye color) and traits of an organism (e.g. brown eyes) that arise from its genotype (Provine 1986). In design, we can discuss phenotypes as the design parameters (*i.e.* the physical attributes of a design), and similarly discuss genotype in terms of the constituent elements design matrix. We specifically build on the Wright (1932) notion of combinations of elements, here design elements, and their interactions giving rise to a fitness landscapes. This conceptualization also maps to a special case of genotype to fitness landscapes, the NK landscape from Kauffman (1971). Many methods exist towards handling these mathematical models. First, we provide the approach of using an approximated landscape.

2.3.2 Generating Gaussian Fitness Landscapes

Altenberg (1997) summarizes findings from Weinberger (1991), Kauffman (1993), and, Fontana, Stradler, Bornberg-Bauer, Griesmacher, Hofacker, Tacker, Tarazona, Weinberger, and Schuster (1993) that demonstrate the NK landscape discussed in Section 2.3.2 follow a statistically normal process for sufficiently intermediate and large values of N and K. Given this finding, the C²D modelling framework adopts a set of additive Gaussian processes $N_k\left(\underline{\mu}\ \underline{\Sigma}\right)$ with a mean vector ($\underline{\mu}$) and a covariance matrix ($\underline{\Sigma}$) for sufficiently sized values of N and K to create a design landscape. Generating these landscapes follows from the general additive model for Gaussian landscapes in the literature (Gallagher and Yuan 2006). This additive technique computes several Gaussian components in the construction of a landscape; this construction results in an overall landscape of N individual Gaussian-components. We use this approach, as well as table approximation for other combinations of N and K, in the construction of the design landscape within the C²D approach. These landscapes build on the additive compilation of multiple random multivariate functions $g(\underline{x})$ as discussed by Gaviano, Kvasov, Lera, and Sergeyev (2003).

$$g(\underline{x}) = \frac{1}{(2\pi)^{n/2}\,\left|\underline{\Sigma}\right|^{1/2}}\, e^{\left(-\frac{1}{2}\left(\underline{x}-\underline{\mu}\right)^T \underline{\Sigma}^{-1}(\underline{x}-\underline{\mu})\right)} \tag{2.8}$$

Where:

n dimensionality of random vector $\underline{x}$

$\underline{\Sigma}$ covariance matrix, $cov(\underline{x}) = E\left[\left(\underline{x}-\underline{\mu}\right)\left(\underline{x}-\underline{\mu}\right)^T\right]$

This approach provides an extensible conceptual depiction of fitness landscapes to those in C²D in general. The fitness function for this model becomes the weighted vector $\underline{x}$ that gives the largest value to the set of multivariate Gaussian functions in equation (2.8). The weights ω influence the heights of each components in this function. These weights randomly vary between $[0, g \cdot r\,]$ where r represents the ratio between the best local optimum and the global optimum, g. Maximizing the fitness of a vector $\underline{x}$ occurs by optimizing these weights to provide the greatest value, as seen in the equation (2.9) and Figure 2.16 below.

$$F(\underline{x}) = \max_i \omega_i \cdot g_i(\underline{x}) = \max_i \omega_i \cdot g_i(\underline{x}) \cdot e^{\left(-\frac{1}{2n}\left(\underline{x}-\underline{\mu}_i\right)^T \underline{\Sigma}^{-1}(\underline{x}-\underline{\mu}_i)\right)} \tag{2.9}$$

The number of Gaussian components m comprising the set ultimately relates to the modality or shape of the space formed. Figure 2.16 demonstrates the formation of a space using three Gaussian components where each component contributes to the construction of the landscape and two of the components result in optima, one global and one local. The process used in constructing these functions and, ultimately the landscape, follows the method from Gallagher and Yuan (2006). The approach establishes a randomly generated m-by-n mean vector $\underline{x}$ of dimension n with m components. These components occur between a lower bound and an upper bound $[l \;\; u]^n$. We similarly relate the design matrix to the factors of this landscape generation approach in the maximally rugged case, through the equating the number of components m to the number requirements within the design space. Following the creation of the mean vector, the method from Gallagher and Yuan (2006) generates a covariance matrix, as see in the above equation (2.8). Construction of the covariance matrix establishes a diagonal matrix S for each m Gaussian component. These matrices then undergo $\frac{n(n-1)}{2}$ rotations between $\pm\,\frac{\pi}{4}$ angles randomly to create an orthogonal matrix T.

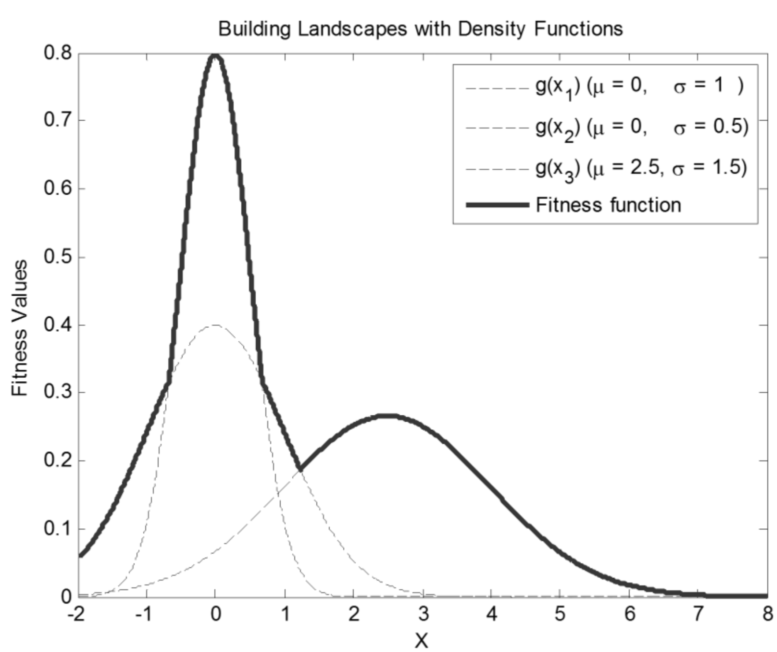


Figure 2.16 Constructing Fitness Landscapes Using Gaussian Density Functions

The product of the transposed orthogonal matrix, diagonal matrix, and the orthogonal matrix defines the final covariance matrix as $T^T \cdot S \cdot T$, as described by the Gallagher and Yuan (2006) approach. The variance values specify the features (e.g. sharpness or flatness) of the peaks, and similarly represent the aspects of the interdependencies K in the context of the C^{2}D approach for design. Figure 2.17 demonstrates this rotation for the elliptical Gaussian function case. By adopting a two-dimension domain to create a 3-dimensional landscape, this approach simplifies to the general corresponding equation for elliptical Gaussian functions:

$$z(x,y) = g * e^{\left(-r_1(X-x_0)^2 + 2r_2(X-x_0)\odot(Y-y_0)+r_3(Y-y_0)^2\right)} \tag{2.10}$$

Where:

g = maximum height of peak

(x_0, y_0) = center of a peak

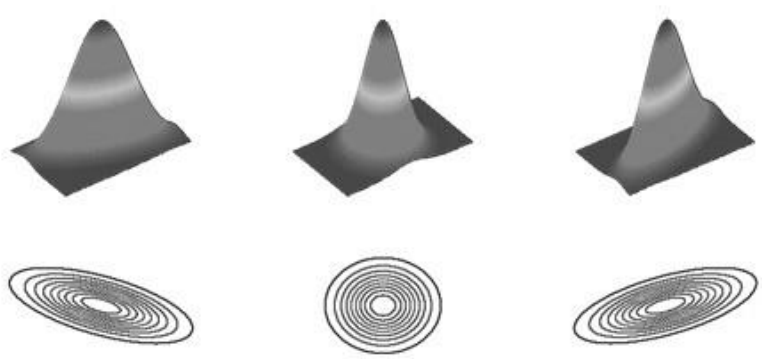
σ^2 = variance

The coefficients of this Gaussian function include:

$$r_1 = \frac{\cos^2\theta}{2\sigma_x^2} + \frac{\sin^2\theta}{2\sigma_y^2} \tag{2.11}$$

$$r_2 = -\frac{\sin 2\theta}{4\sigma_x^2} + \frac{\sin 2\theta}{4\sigma_y^2} \tag{2.12}$$

$$r_3 = \frac{\sin^2\theta}{2\sigma_x^2} + \frac{\cos^2\theta}{2\sigma_y^2} \tag{2.13}$$



$\theta = \frac{-\pi}{4}$ $\quad$ $\theta = 0$ $\quad$ $\theta = \frac{\pi}{4}$

Figure 2.17 Rotation of Gaussian Component by θ with $\sigma_x^2 = 1.56, and\ \sigma_y^2 = 6.25$

This approach from Yuan and Gallagher (2006) provides a tunable landscape generation mechanism based on six possible parameters that, when modified, offers a relevant methodology for approximating the NK landscape in the $8 \geq K < N - 1$ cases. The $K = N - 1$ case follows a completely random assignment of values across the design; similarly, the $K = 0$ case corresponds to a multi-locus model that typically results in a single globally attractive optimum, *i.e.* the smooth Mt. Fujiyama model (Kauffman 1993). These six tunable parameters for the Gaussian landscape include the dimensionality of the landscape (n), the number of Gaussian components in the landscape (m), the upper boundary of the search space (u), the lower boundary of the search space (l), the value of the global optimum (g), and the ratio between fitness values of the best local optimum and the global optimum (r). The additive composition of Gaussian processes enables the quick creation of a landscape that approximates the problem of genotype to fitness landscapes discussed as part of C^2D (Altenberg 1997).

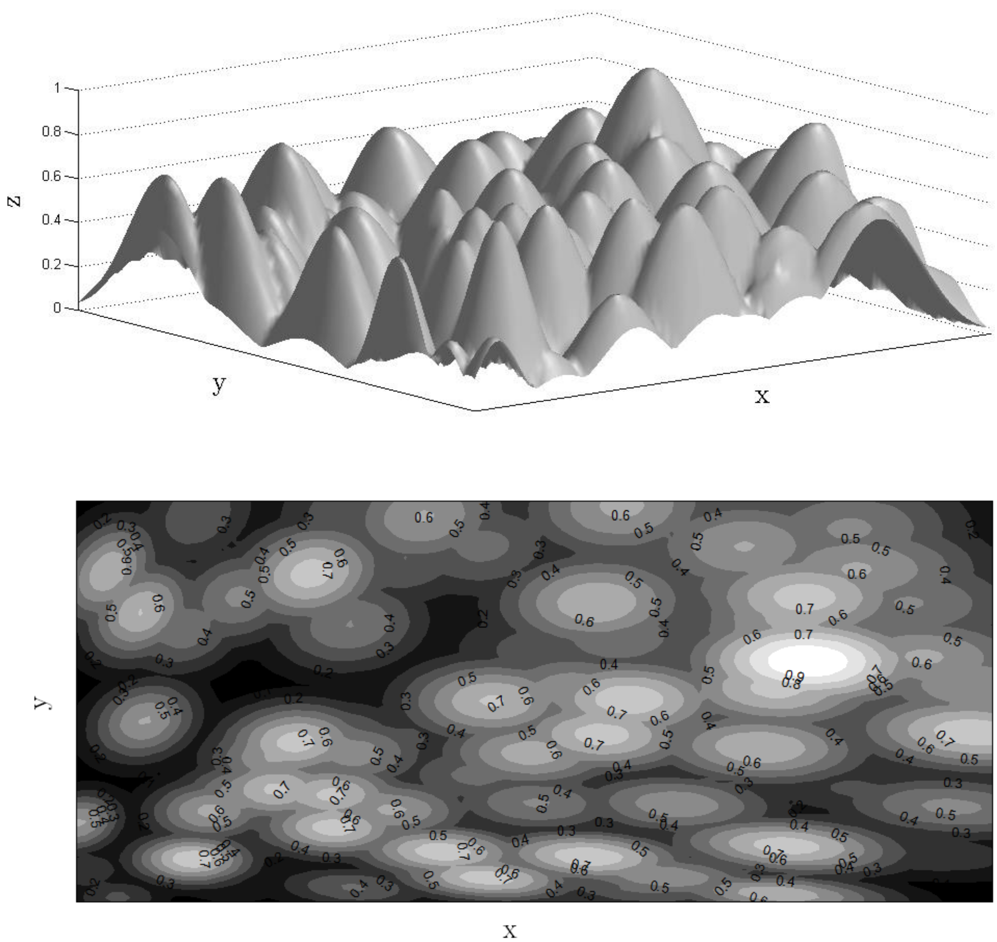


Figure 2.18 Tunable Gaussian Landscape with 100 Gaussian Components

Figure 2.18 provides an example landscape using this technique in MATLAB (cf. Appendix C). This generalized approach can only approximate the complex relationships of these landscapes for intermediate values of K and only partial estimation for low levels of K between components. For mapping the relationships and interactions between the design parameters and functional requirements that give rise to design complexity we also use and examine other approaches, such as the use of tables to approximate the NK class of landscape. The use of the NK approach allows the research to relate the number of design elements and functional requirements N and their interactivity K, without requiring the direct specification of the search space boundaries, to theoretical design fitness values. As part of the C^2D framework, the research considers complexity as a measure relating these two quantities, specifically through the density of the local optima, or more formally $K/N - 1$. The research provides a more comprehensive list of other possible measures of complexity derived from the literature in Section 2.3.4

2.3.3 KAUFFMAN'S NK MODEL AND THE RUGGED LANDSCAPE

One of the most promising landscape models for benchmarking engineering design performance relative to system complexity comes from the highly tunable and rugged landscape known as the NK model, a special subset of *fitness landscapes* developed by Kauffman (1971). In the NK formulation, the ruggedness of the landscape arises from the interactions of tunable parameters. These parameters include the number of characteristics of an entity (N), the degree of interactions between these entities (K), and the possible states that this characteristic can occupy (A). The fitness of a single point on these landscapes approximate a normal distribution for sufficiently large values of N with a mean of $\frac{1}{2}$ and variance of $\frac{1}{12\,N}$ (Skellett, Carins, and Geard 2005).

2.3.3.1 NK EXAMPLE FROM BIOLOGY

Biologists label the interactivity between entities or elements of a biological system as epistasis, defined as the interaction of genes controlling phenotype expression. Figure 2.19 demonstrates the concept of epistasis using a Punnett square for the dihybrid cross of mice affecting coat color as described by Kowles (2001). In the example, two brown mice with banded coats (controlled by the presence of an Agouti gene) reproduce. Both of the original mice have heterozygosity on both alleles of the square. The figure demonstrates that the influence of epistasis between two loci controls the coat color of mice in this cross, and results in the possibility of albino offspring.

Locus B – determines whether hair is banded in color

- *Dominant allele (B)* results in hair with bands and an **agouti** (brown) coat
- *Recessive allele (b*) results in having no bands and a **black** coat if homozygous

Locus A – determines the ability to produce pigmentation

- *Dominant allele (A)* results in normal pigment production
- *Recessive allele (a)* blocks all pigment production, resulting in an albino, if homozygous

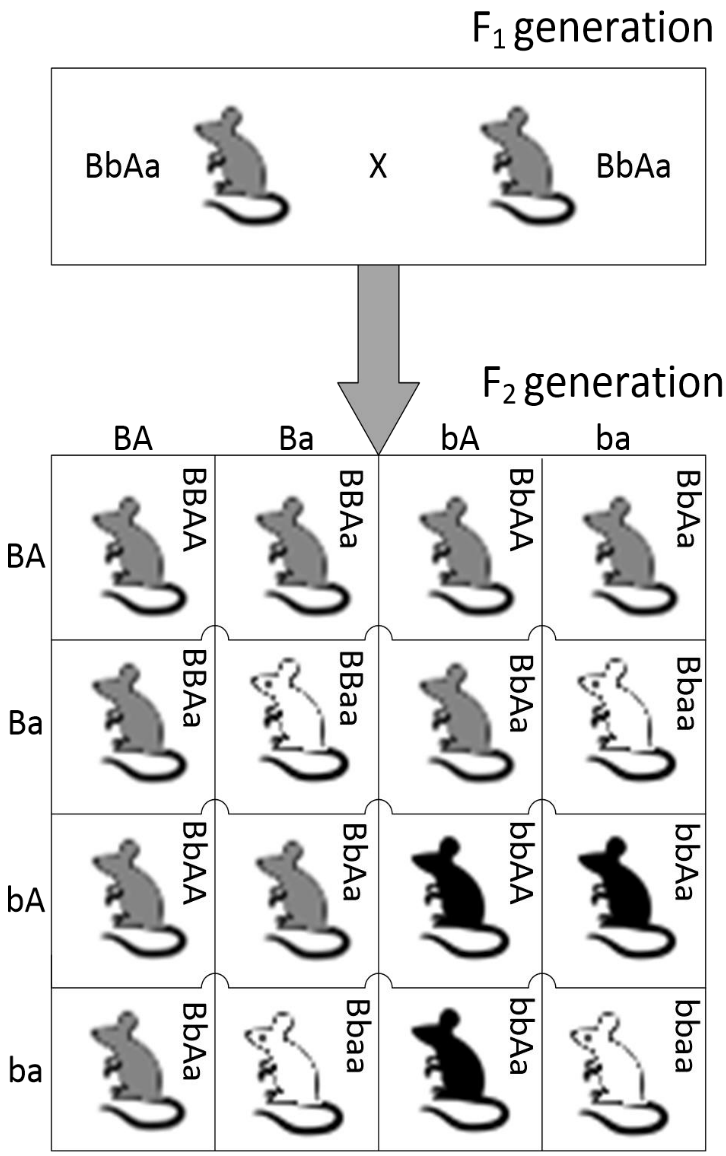


Figure 2.19 Epistatic Interaction Resulting in Albino Mice (9:3:4 agouti:black:albino)

The Kauffman and Weinberger (1989) model establishes $K = 0$ as the smoothest possible landscape and $K = N - 1$ as a maximally rugged landscape. In the above example, $K = N - 1$ as a mutation at locus A has the effect of changing the overall fitness contribution of locus B. However, in the event of $K = 0$, each locus would have independent contributions to the fitness of the biological entity, resulting in no interactions between alleles.

2.3.3.2 Factors of NK

Kauffman and others in the field of complexity science commonly employ these models to explore the role of complexity. By using K as a tunable parameter, experimenters explore the transition region between order and chaos, where a theoretical maximal fitness occurs on the "edge of chaos" between the two zones (Frenken 2006). As K increases, landscapes becomes increasingly chaotic (i.e. neighboring points become uncorrelated). In this event, a large number of local optima appear and tend towards the mean fitness of the landscape. The interlinked nature of these spaces lead to intractability and, in the words of Kaufmann a "complexity catastrophe" where no one solution can emerge. As part of C^2D, we look towards complexity as a measure of the density of local optima, or more formally as $K/N - 1$. We provide a more comprehensive list of possible measures of complexity, as part of Section 2.3.4.

Figure 2.20 highlights the concept of the edge of chaos within the domain of complex adaptive systems, which we extend through analogy to include the design process. This example supports the extensibility of the NK landscape beyond the domain of biological principles and into the organizational and complex systems domain. Figure 2.21 provides insight into the role of epistasis (i.e. interconnectedness) on general landscapes. Figure 2.22 similarly demonstrates the worst-case scenario, *i.e.* the "complexity catastrophe," of a fully uncorrelated landscape. We use the C^2D model developed as a part of this research to generate these figures for illustrative purposes and to highlights its desirability for use in general optimization and search problems. Mathematically, the appeal of the NK model in the field of optimization stems from its nature as a simple model of nondeterministic polynomial time complete problems (NP-C). Another word, NP-C decision problems remain nondeterministic polynomial time problems and remain reducible in polynomial time. Ultimately, for our purposes, these NK landscapes represent stochastically generated fitness functions on bit strings. From an evolutionary dynamics perspective, these landscapes provide multiple domains of attraction through the event of bit-flipping mutations and recombination. The

NK model defines a combinatorial phase space consisting of every string, S, of length, N. This length, N, corresponds to the number of loci (i) within a genotype, x. Each string in this this search space adopts a scalar fitness value $F : \{0, 1\}^N \rightarrow \mathbb{R}^+$ on a binary string where $x \in \{0,1\}^N$. This binary value for the x genotype corresponds to the two possible number of alleles that each locus (x_i) may adopt. Commonly, in this framework, a "1" may correspond to a beneficial mutation, whereas a "0" may correspond to a deleterious mutation.

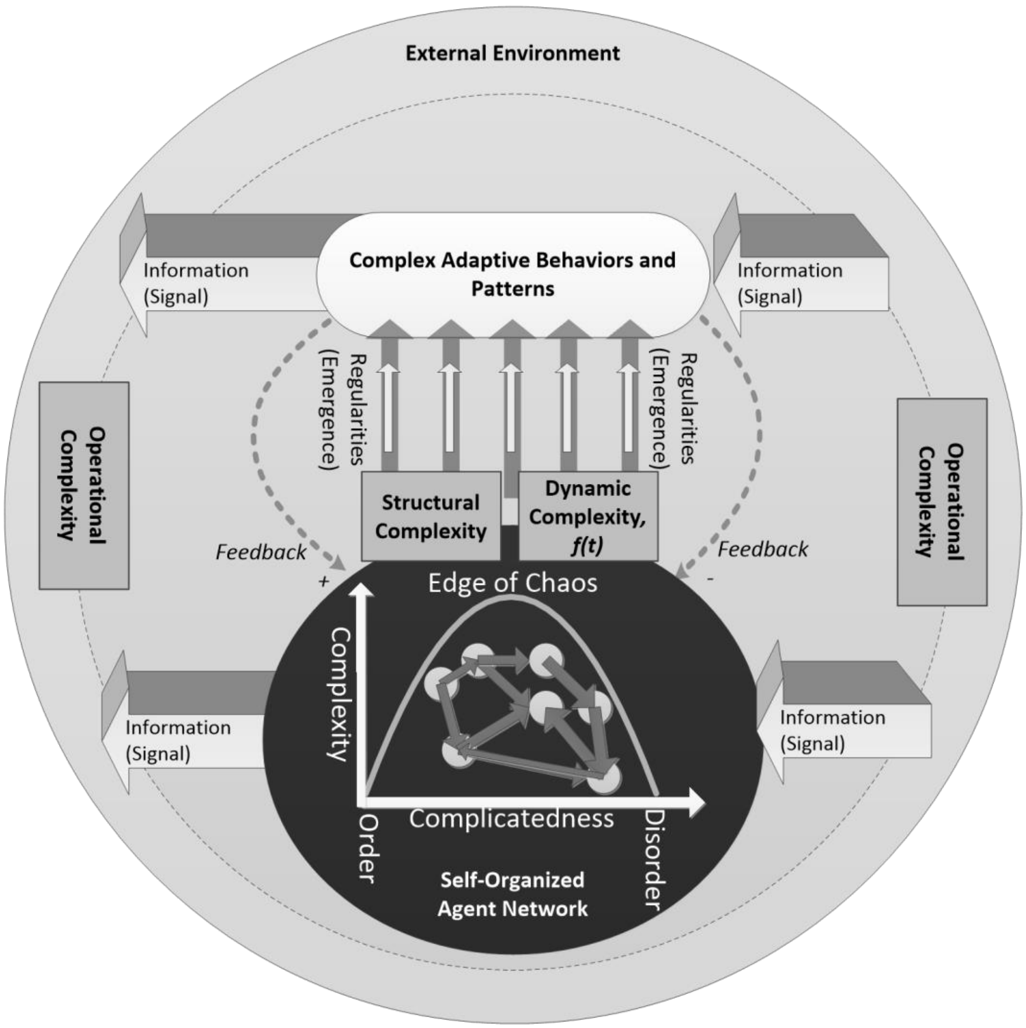


Figure 2.20 'Edge of Chaos' as Related to the Concepts of Complex Adaptive Systems. The edge of chaos rests between disorder and order, and gives rise to complexity. Structural complexity tends toward the ordered side of the complicatedness spectrum and dynamic complexity tends to arise from the disordered sided of the complicatedness spectrum. In this conceptualization, complicatedness defines the ability of decision-makers to contend with complexity. The system influences the environment and adapts to changes in the environment. Emergence results from the patterns of behaviors that form between the self-organized agent network, which itself provides feedback to the system. Operational complexity represents the category of complexity involved at the edges, driven by the number, diversity, and strength of external interactions.

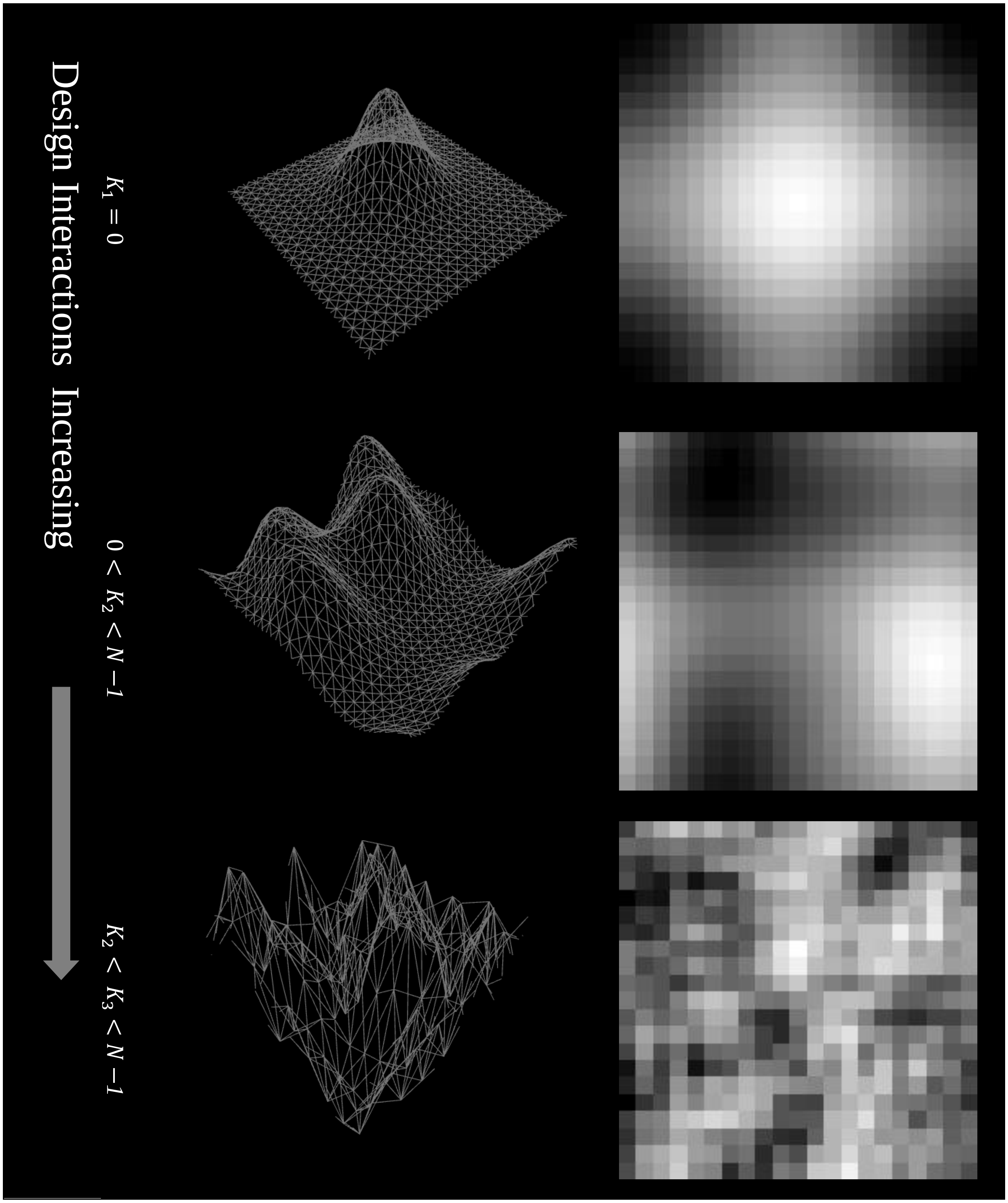


Figure 2.21 Design Interactions Analogy to Epistasis and the Landscape. This figure was generated using the C²D model with the 3D landscape from the model (left) and the equivalent gradient representation used in simulation runs (right). Vertical peaks, *i.e.* less shaded or grayed regions, represent higher fitness. In biology, the horizontal axis represent biological parameters being measured (e.g. component of phenotype, genotype, and nucleotide sequence combinations).

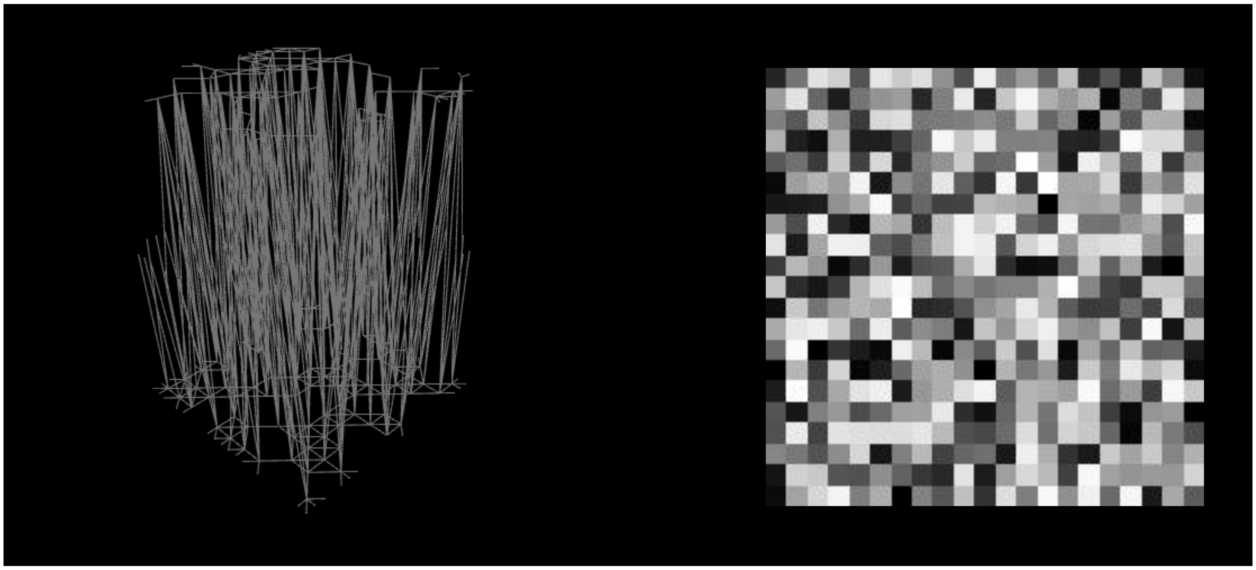


Figure 2.22 Epistasis in the C2D model for $K \cong N - 1$

Fitness values in the *NK* context represents the average contribution of N fitness components (F_i) by each locus (i) in the string. These fitness values arise from each gene's allele (x_i) contribution, as well as the alleles at K other loci, which describes the degree of interactivity or epistasis within the genotype. Weinberger (1991) found these expected fitness values on a string normally distributed for situations with sufficiently large degrees of interactivity. Kauffman (1989) provides the general mathematical representation of the fitness function $F_i(S)$ as a mapping between strings of length $K + 1$ and scalar values (i.e. fitness contributions). This relationship follows as:

$$F(x) = \frac{1}{N}\sum_{i}^{N} F_i(S) \tag{2.14}$$

$$S = x_i;\ x_1^i, \dots, x_K^i \tag{2.15}$$

Where:

$$\{i_1, \dots, i_k\} \subset \{1, \dots, i-1, i+1, ..N\}$$

In this model, the fitness of the genotype is the average of N fitness components $f_i(S)$ contributed by each locus i of the genotype. This model ensures that the individual fitness components depend on themselves and on K other epistatic loci. This basic model posits a 'House of Cards' relationship for epistasis where any mutation must influence all fitness components with which the locus interacts, regardless of distance (Kingman 1980). This relationship means that any mutation in any of the genes affecting a fitness component results in no information passage from the past after the mutation event occurs, and, as suggested by its name, these mutations results in the collapse of the original fitness profile and the creation of new profiles. Ongoing mutation events, in effect, translate into the need for a dynamic fitness landscape. The environment in a biological context often drive these mutations and adaptions through a variety of simultaneous selection pressures. These pressures often conflict and compete in the evolution of a biological entity; these tradeoffs often include balancing traits such as versatility, *e.g.* the ability of an organ to perform multiple functions, and performance, *e.g.* the ability of an organ to perform a function well. These interactions lead to the biological principle of 'frustration' (i.e. simultaneous optimization of multiple related factors) where beneficial changes to one allele at an interacting locus may degrade the fitness of another allele at a different interacting locus leading to compromised solutions to a conflicting set of needs (Niklas 1997). This concept directly parallels the issue of overcoming complexity in engineering design; specifically it mirrors the conceptual elements of Pareto optimality in design, *i.e.* impossible to improve the fitness of one design parameter without making at least one other worse off.

Altenberg (1997) provides a generalized mapping of the NK model. As opposed to the model in equation (2.14), this model generalizes the relationship between one gene and one fitness component by taking advantage of the symmetric effect between a gene and the other K loci. In this construct, the model provides a mapping between a set of N genes and a set of f fitness components. This mapping represents in effect a weighting index set $\{j_1(i), j_2(i), \dots, j_{p_i}\}$ or matrix that replaces K as a prime variable. This generalized relationship for fitness follows:

$$F(x) = \frac{1}{f}\sum_{i}^{f} F_i(S) \quad (2.16)$$

$$S = x_{j_1(i)}, x_{j_2(i)}, \dots, x_{j_{p_i}} \quad (2.17)$$

Where:

p_i the number of genes affecting a fitness component i

$j = 1 \dots N$ the number of genes affecting a fitness component i

$i = 1 \dots f$ the fitness components controlled by gene j

$\{j_1(i), j_2(i), \dots, j_{p_i}\} \subset \{1, \dots, N\}$

Altenberg (1996) captures the gene-fitness mappings $\{j_1(i), j_2(i), \dots, j_{p_i}\}$ through a matrix M. This matrix comprises elements $[m_{ij}]$ relating genes and fitness components. The rows of the matrix (i.e. $p_i = [m_{ij}]$ with $j = 1 \dots N$) relate the controlling genes to each fitness component i. The number of genes affecting these fitness components represents polygeny in genetics, which measures the contribution to fitness from multiple genetic components. Similarly, the columns of the matrix (i.e. $p_j = [m_{ij}]$ with $i = 1 \dots f$) provide the fitness components controlled by each gene j. This p_j column vector represents each gene's pleiotropy. In genetics, pleiotropy measures the influence a single gene exerts on multiple fitness components.

$$M = [m_{ij}], i = 1 \dots f, j = 1 \dots N \tag{2.18}$$

Where:

$m_{ij} \in \{0,1\}$

$j = 1 \dots N$ the number of genes affecting a fitness component i

$i = 1 \dots f$ the fitness components controlled by gene j

This relationship provides an extensible conceptual bridging mechanism for the later discussion of design. The generalized form of the NK model also allows for the introduction of weights (λ_{ij}) by modifying $m_{ij} \in \{0, \lambda_{ij}\}$ and $0 < \lambda_{ij} \leq 1$. This modification also enables future research focused on adopting the C^{2}D framework to value engineering where design elements and their interactivity represent a range of value propositions.

Table 2.3 Example of Weighted Gene-fitness Mapping between Two Fitness Components, $f = 2$, and Three Genes, $N = 3$, where $m_{ij} \in \{0, \lambda_{ij}\}$

		Genes, j *(Pleiotropy)*		
	m_{ij}	m_{i1}	m_{i2}	m_{i3}
Fitness Components, i *(Polygeny)*	m_{1j}	$m_{11} = \lambda_{11}$	$m_{21} = 0$	$m_{31} = \lambda_{13}$
	m_{2j}	$m_{12} = 0$	$m_{22} = \lambda_{22}$	$m_{32} = \lambda_{23}$

2.3.4 *Measures of Complexity*

Ultimately, we use the *NK* landscapes to provide an intuitive analogy to represent complexity as in design. We have defined complexity for our purposes to this point as the degree of interdependencies between design elements. However, many additional approaches exist for measuring and describing this concept of complexity. For completeness, we provide some additional background into this area; however, ultimately the heuristic value of the landscape approach remains intact across these various measures.

As seen earlier, measures of a design size do not adequately describe the nature of the interactions and fails in consistently describing or, more importantly, quantifying complexity. For example, in the context of biological systems, the evolution of biological complexity posits a central outcome in the process of evolution; however, this complexity remains difficult to measure and define. Specifically, consider the paradox that an organism's complexity does not directly relate to the amount of deoxyribonucleic acid (DNA) or the genome size as measured by the C-value, the amount of pictograms of DNA within a somatic or nucleic cell. Literature from genetics research refers to this as the C-value paradox or enigma (Thomas 1971). In essence, this C-value paradox refers to the fact that single cell organisms can have vastly larger C-value than even the most popularly considered complex organisms, like humans. For example, the unicellular *Amoeba dubia* contains more than 200 times the DNA of humans (Gregory and Hebert 1999). However, despite the unicellular Amoeba having more DNA, it actually comprises non-coding DNA. This non-coding DNA lacks information content or genes, in turn limiting the number of interacting elements. Tying this into previous discussions on design complexity, this lack of interacting elements plays a central role in the mitigation of complexity. This lack of interaction in a biological sense also leads to less complex genetic behavior. Interestingly, as seen in the discussion of part counts and complexity, the findings from the natural world show that even though a general relationship between complexity and the amount of DNA exists, direct correspondence between size and complexity does not always hold. Figure 2.23 reproduces a representation from Vickers (2007) of the trend of complexity in encountered in the biological realm over the course of evolution. Unlike the complexity in the engineering design sense, complexity from an evolutionary perspective often results in advantageous adaptations, and these benefits underscores the need for research into not only mitigating design complexity, but also harnessing it.

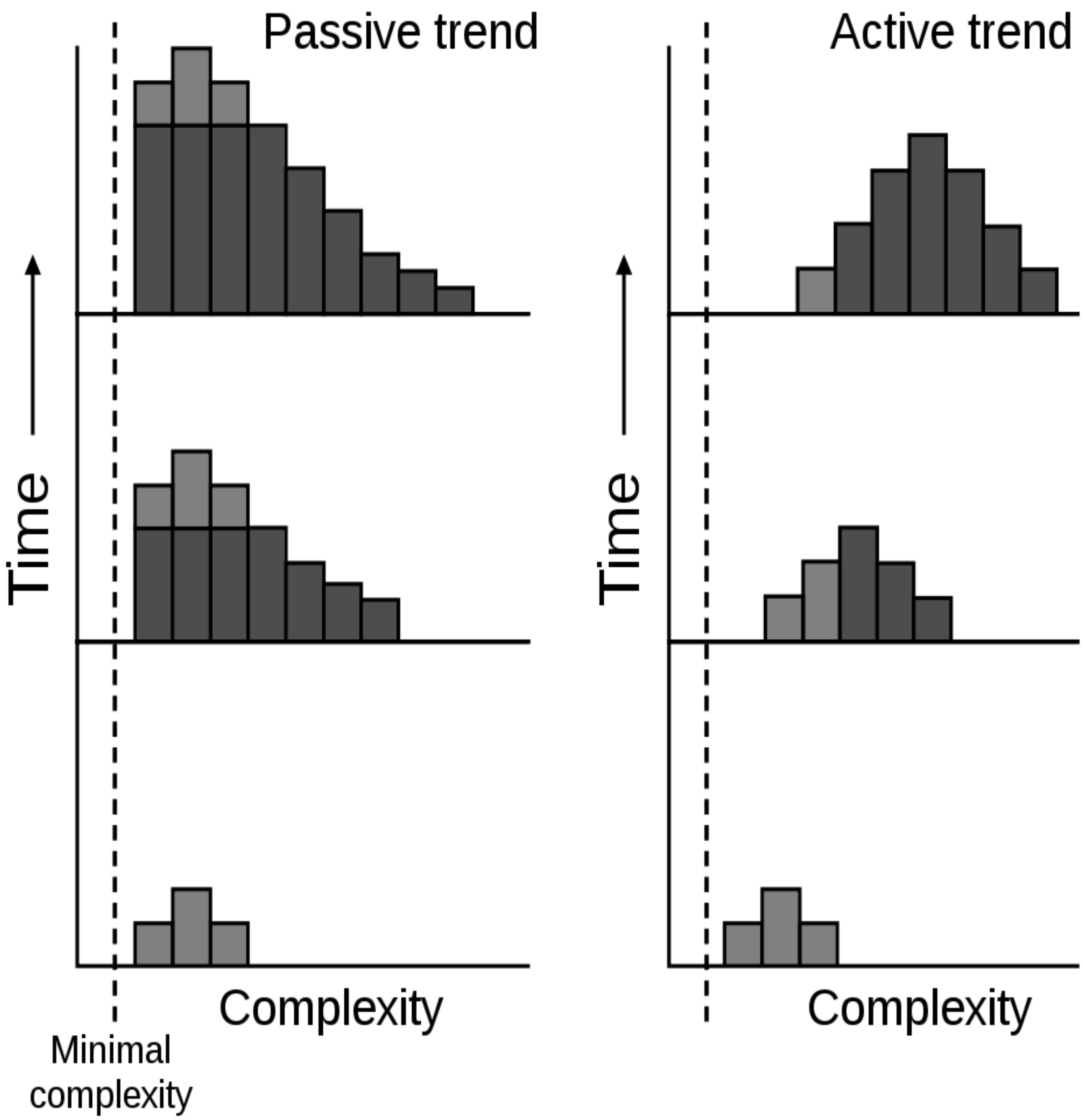


Figure 2.23 Evolution of Complexity. Reproduction, with permission, of the evolution of complexity by Vickers (2007). This graphic provides an overview of two perspectives of complexity in the context of biology and evolution: the passive trend (left) and the active trend (right). The passive trend demonstrates the characteristics of complexity growing as the result of pure variation, as seen this perspective provides results in a stable mode and complexity only increases in a relatively small portion of biological entities. The active trend demonstrates the concept of evolutionary self-organization, where systemic complexity increases and gives rise to emergent properties. In this event, the complexity of distribution gradually favors increasingly complexity. The active trend currently stands out in the literature as the most likely case for evolutionary complexity (Furusawa and Kaneko 2000; Adami, Ofria, and Collier 2000). In either case, genetics points out the inevitability of increased complexity over the course of time and evolution.

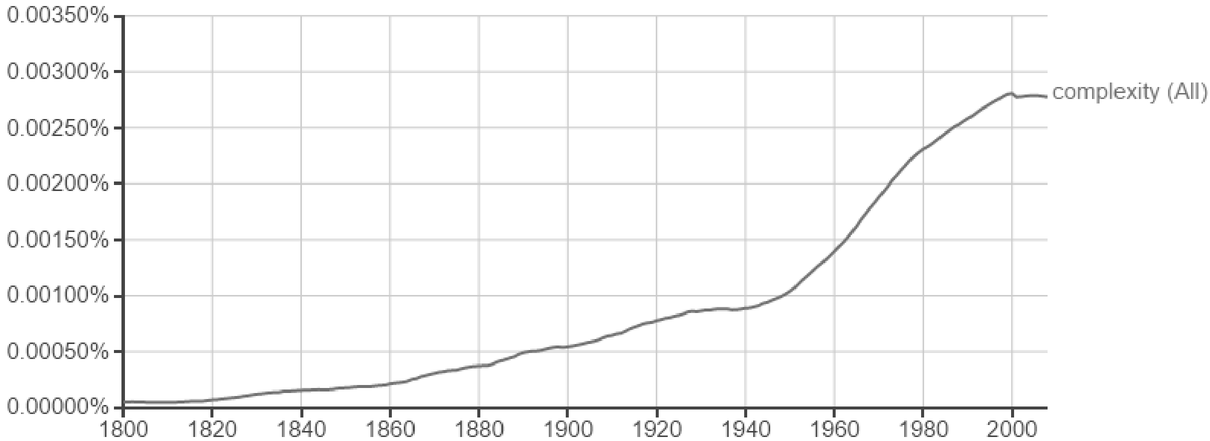


Figure 2.24 English Word Usage Statistics for Complexity from 1800 to 2008. This figure was developed using the © 2013 Google books Ngram Viewer tool (surveys use percentage over all electronically catalogued book holdings within Google).

These same general trends, relationships, and anomalies with regard to complexity also occur across physical and engineered systems, as well organizations. In the most general case, complexity shares the common characteristic of a system containing multiple interacting elements and subsystems that result in an unknown output or behavior for the system; this unexpected system behavior makes the system difficult to understand and characterize a-priori (Scuricini 1988). The universality of these characteristics motivates the wider scientific investigation of complexity science. Figure 2.24 shows that despite the origin of the word complexity dating back to the eighteenth century, its usage has recently seen an insurgence. However, its usage remains vague and imprecise (Bennett 2003). Murray Gell-Mann (1995) helps to define complexity by tracing its meaning to its Latin root, plexus meaning braided or entwined, and subsequently to the English root complexus, meaning braided together. In order to specify its meaning more precisely we similarly established its definition as the interdependency between entities, and design complexity, more specifically, to mean the interdependency between design elements giving rise to design uncertainty. Suh (1990) refers to this design uncertainty as the probability of not meeting the specified design requirements.

Unsurprisingly, many businesses and organizations, including those with a prolific international presence, share many of the same conclusions as those derived from biological systems regarding complexity. These findings include that the number of additional organizational parts, such as locations do not necessarily make their business operations more complex. Rather findings from Muller and Woods (1994) show that most business operations finds that change driven by the number of interdependencies and externalities create the largest sources of complexity for an organization. For example, the addition of a new coffee shop in a large chain does not necessarily raise the complexity for a corporation. In the organizational context, internal changes such as a new product offering and changes in consumer tastes represent the largest challenges for management (Muller and Woods 1994). These dynamic changes lead to the continual collapse of the existing landscape and the creation of new fitness landscapes; these new landscapes require adaptions (i.e. mutations) to the existing business models and strategies, very much in the vein as a biological entity. As seen previously in Figure 2.20, these forms of complexity often include three primary forms: structural, dynamic, and operational. Table 2.4 summarizes these types of complexity and provides a distinction for how they differ from complicatedness.

Table 2.4 Characteristics of Complexity Types from Literature

Structural or Static Complexity	▪ Number, diversity, complicatedness, and interconnectivity of components internal to the system in steady state (Wall 2009) ▪ Accounts for the resources and their state, and its measure provides a scheduling tool for resources (Calinescu et al. 2000)
Dynamic Complexity	▪ Number of different states for the system and the associated probabilities of components being in that state (Wall 2009) ▪ Consists of programmable (i.e. deterministic) elements (e.g. predicable state changes) and non-programmable (i.e. stochastic) elements (e.g. equipment failures) to be managed (Frizelle 1996) ▪ Complexity for systems with coupling and high rates of dynamism (i.e. rates of change) will increase (Perrow 2002; Perrow 2007)
Operational Complexity	▪ Number, type-diversity and strength of interactions with external systems (Wall 2009) ▪ Behavior of a system during its operations; operational complexity measures monitor operational system performance, such as at a manufacturing facility (Calinescu et al. 2000)
Complicatedness	▪ Multiple components and/or connections (Wall 2009) ▪ Minimum information needed to uniquely define a system (Gell-Mann and Lloyd 1996) ▪ Capacity for a decision making unit to manage the level of complexity in the system, *i.e.* the number of complex factors a decision maker can consider (Tang and Salminen 2001)

Each of these sources of complexity exist in engineering design.[15] By comparing the definitions and characteristics of complexity from natural systems and organizational systems, we similarly find shared characteristics of complex systems applied to descriptions of complexity in engineered systems. These shared characteristics include:

- Correlation to number of components and elements (Suh 1990; El-Haik and Yang 1999)
- Performs a large variety of functions (Orfi, Terpenny, and Sahin-Sariisik 2011)
- Multiple levels of interactions and interdependencies (Baldwin and Clark 2006)
- Cognitive difficulty to understand across life cycle (Summers and Shah 2003)
- Unclear cause and effect relationships between system elements (Summers and Shah 2003)

Ultimately, understanding the cognitive difficulty experienced when attempting to design an engineered system requires some formalism and quantification. Managing complexity requires an understanding of complexity sufficient to measure it; metrics for complexity across the life cycle (i.e. design, manufacturing, maintenance, operations, sustainment, and disposal) remains a major thrust of research (Bashir and Thomson 1999). Metrics provide a means for condensing and representing quantitative or qualitative measurable aspects of an issue (Horváth 2003; Kreimeyer, Bradford, and Lindermann 2010). Metrics offer a useful encapsulation of information regarding an actual system, individual component, or the environment. Measurement theory, a branch of applied statistics, provides methods to build basic metrics that describe real phenomenon through a mapping of empirical objects to analytical conceptualizations (Steven 1946; Allen and Yen 2001). Table 2.5 provides an overview of complexity metrics that go beyond the discussion from axiomatic design (cf. section 2.1.2). This table highlights a cross section of approaches and paradigms for handling complexity that all share many similar characteristics; we provide the table in part to establish the theoretical need for additional research to derive a unified framework extensible across domains

[15] We relate structural complexity to the number of design elements, specifically the number of functional requirements and design parameters. Design often faces changing conditions, requiring an ongoing learning process to ensure exploration keeps pace with the changing design landscape. These changes represent state changes to the system. Changing requirements and unexpected changes to the design approach often introduce these sources of dynamism. With the delivery of a product or engineered system new sources of complexity arise from, called operational complexity. Operational complexity specifies the complexity arising due to interactions with the external environment.

Table 2.5 Complexity Measurement Tools and Metrics in the Literature

<table>
<tr><th></th><th></th><th>Technique</th><th>Description</th></tr>
<tr><td rowspan="3">Tools</td><td rowspan="3"></td><td>Structural equation modeling (Schwandt 2010)</td><td>Statistical technique for estimating causal relations using a combination of statistical data and qualitative assumptions for causal relationships</td></tr>
<tr><td>Exploratory Factor Analysis (Schwandt 2010)</td><td>Multivariate statistical regression modeling technique to uncover underlying structure of a large set of variables by searching for variability among variables to detect unobserved influences</td></tr>
<tr><td>GQM/BSC (Kreimeyer 2010)</td><td>Goal-Question-Metric (GQM) and Balanced Scorecard (BSC) can be implemented, similar to Quality Functional Deployment (QFD) approaches to identify interdependencies</td></tr>
<tr><td colspan="4"></td></tr>
<tr><td rowspan="5">Metrics</td><td rowspan="5">Computer Science and Software Engineering</td><td colspan="2">Lines of Code (LOC) as a measure the size of a program (Azume and Mole 1994)
$C \propto Lines\ of\ Code$</td></tr>
<tr><td colspan="2">Kolmogrov complexity measures the shortest path through a program for a given output (Cardoso 2006).
$K_L(w\ outputs | x\ inputs) = min(Program_{length})$</td></tr>
<tr><td colspan="2">Cyclomatic Number provides the number of paths through a program required to visit all nodes, providing a number for the decision points. This metric shows that a threshold of 10 as the maximum number of decision nodes per software module (McCabe 1976).
$C = Number\ of\ edges - Number\ of\ nodes + 1$</td></tr>
<tr><td colspan="2">Information flow complexity provides a function of the complexity based on the logical flows of the coding. Fan-in represents the quantity of local flows into the procedure plus the number of data structures from which that procedure retrieves information. Similarly, Fan-out represents the quantity of local flows out of the procedure plus the number of data structures that the procedure updates. Local flows provide data passed to and from procedures (Henry and Kauri 1981).
$C = Procedure\ Length \times (fan - in \times fan - out)^2$</td></tr>
<tr><td colspan="2">Halstead complexity measures, introduced by Halstead (1977), relate static and measurable aspects of code, such as the number of distinct operators (η_1) and operands (η_2) to their respective totals (N_1) and (N_2) in order to understand code complexity.
$Difficulty = {}^{\eta_1}/_2 \times {}^{N_2}/_{\eta_2}$
$Effort = Difficulty \times (N_1 + N_2) \log_2(\eta_1 + \eta_2)$</td></tr>
</table>

Table 2.5 Complexity Measurement Tools and Metrics in the Literature (Continued)

Metrics	*Computer Science and Software Engineering (Continued)*		*Defect density*, the number of defects per module of a program provides a measurable attribute of error-prone pathways and through analogy the complexity of the code (Zuse 1998). $C \propto {}^{defects}/_{module}$
		Object-oriented Programming (Wand and Weber 1990)	*Methods per class* provides the summation of all other method-related metrics for complexities to estimate the complexity of the class as a whole and indicates the development and maintenance effort for the class (Wand & Weber 1990).
			Source lines of code (SLOC) measure the quantity of lines in software, best corresponding to our concept of complicatedness (Boehm 1981).
			Function points (FPs), most similar to C^2D, estimates the amount of functionality within software as a measure of complexity (Kunkler 1983).
			Depth of inheritance tree measures the embedded elements of a program inherited by its hierarchy (e.g. previous classes). It provides an estimate for the possible propagations and impact to the code associated with a code change (Wand and Weber 1990).
			Number of children measures the quantity of successors of a class to estimate the possible impact that changes within a program may have when reaching back a on a particular class through (Wand and Weber 1990).
			Coupling between object classes calculates the number of other classes that share a relationship in order to provide an estimate about program errors and to understand the program structure (Wand and Weber 1990).
			Response for class metric represents the size of methods of a class that respond to a specific message, this provides a run-time complexity metric (Wand and Weber 1990).
			Lack of cohesion compares variables and methods to estimate the need to decompose a class further (Wand and Weber 1990).
	Information Theory		*Information entropy* provides a measure for the relative disorder of a system ($H(X)$), used originally to express disorder in regards to information content (I) derived from telecommunication theory and related to Shannon's law (Shannon and Weaver 2002). This theory provides a fundamental basis for the Axiomatic approach and definition of complexity by Suh (1990). $H(X) = E[I(X)]\,, \quad I = \sum p_i \log \frac{1}{p_i}, \quad H(X\|Y) = \sum_{i,j} p(x_i, y_j) \log \frac{p(y_j)}{p(x_i,y_j)}$

Table 2.5 Complexity Measurement Tools and Metrics in the Literature (Continued)

Metrics	*Information Theory in Computing*	*Sheppard complexity* modifies the *information flow complexity* metric from Henry and Kafura (1981) stated above to remove the length of a procedure as a driver of complexity. This metric has wide spread use outside of just code assessments, as it provides a measure for the logical exchange and interconnectedness of information. $$C = (fan-in \ \times fan-out)^2$$
		Oviedo's data flow complexity attempts to measure the complexity of information by including control-flow and data-flow measures together (Oviedo 1980). The control-flow represents the number of edges and the data-flow represents the number of variables referenced but not defined in a program block (i.e. sequence of statements between branches). The later provides a look into the interdependencies of code elements. $$C = Edges + \sum_{i}^{n} External\ Variables_i$$
	Engineering	*Number of requirements* provides a proxy for complexity due to its correlation to the number of requirements, and, its subsequent translation to increase numbers of stakeholders, potential variety among users, further developers, more subcontractors, additional product features, and new external interfaces (Regnell, Sevensson, and Wnuk 2008). $$C \propto Number\ of\ Requirements$$
		Product complexity index, an index tied to the summation of various dimensions of perceived complexity sources (e.g. variety, functionality, structural, design, production), provides an overall view of the relationship between production complexity and manufacturing concerns (Orfi et al. 2011). $$C = \sum_{i=1}^{n} Complexity\ Indices_i$$
		Mendling Process Complexity provides an index that relates a process size, density, partitionabilty, connector interplay, concurrency, and cyclicity to its overall complexity (Mendling 2008).
	Cognition	*Cognitive Weights* describe the difficulty of understanding a task (Gruhn andLaue 2007). Work by Vanderfeesten et al. (2008) helped to augment this approach by including coupling and cross-connectivity consideration. Similar metrics include relating the goal-question-metric to its understandability (Ghani et al. 2008).

2.4 DESIGN-TEAMS AS COLLABORATIVE SYSTEMS

The complexity of the design space represents only one of the necessary components in developing a broader design performance perspective; another key factor for a successful design effort, regardless of its complexity, is the strength of the designers and their collaborations. In essence, these collaborations necessitate that most design occur in the context of teams. We adopt the definition a team from the work of Cohen and Bailey (1997) who builds on Hackman (1987) and Alderfer (1977):

> *"A team is a collection of individuals who are interdependent in their tasks, who share responsibility for outcomes, who see themselves and who are seen by others as an intact social entity embedded in one or more larger social systems (for example, business unit or the corporation), and who manage their relationships across organizational boundaries."*

We consider these formed teams, *i.e.* design-teams, as the supremal decision-making unit for design; this unit achieves its objectives through the realization of the overall design objectives. This unit acts as an overall coordinator in the design process to minimize the agency costs associated with discrepant goals and objectives of the infimal unit, *i.e.* the individual designer decision making units.[16] We adopt the concept of supremal and infimal decision-making units from the economics literature to help highlight the joint decision-making nature of the design process (Arrow and Hurwicz 1960; Hurwicz 1960; Hurwicz 1971; Takahashi, Kijima, and Sato 2004). At the core of these relationships rests a dynamic process between infimal units. Within context of the developed framework, these infimal units, who represent members of the collaborations, strive to improve their local fitness values. However, over time, constraints placed by the larger team, or the supremal unit, impose restrictions and constraints with the goal of reaching pre-defined fitness goals or global optima. As discussed, the exchanges between the infimal units represent collaborative socio-technical interactions, which enable the exploration of the design landscape.

The literature has widely explored how the structure of teams relates to performance (Gladstein 1984; Hackman 1987; Manz 1990; Manz 1992; Wageman 1995; Cohen and Bailey 1997; Stewart and Barrick 2000). In particular, the literature strongly supports the relationship of structural

[16] We base the definition of agency cost around work from Holmstrom (1982); defining it as the conflicts that arise between an organizational entity, such as a team, and its constituent parts when these constituent parts act on divergent interests, usually self-interest, from the entity.

characteristics of a team (e.g. the allocation of tasks, responsibilities, and authority) to the overall performance of teams (Hackman 1987; Wageman 1995; Cohen and Bailey 1997; Stewart and Barrick 2000). Additionally, Stewart and Barrick (2000) found that teams with higher self-leadership performed better when performing conceptual tasks, for which the process of design qualifies. However, as suggested by Stewart and Barrick (2000), the ideal team structure remains highly sui generis and contingent to the tasks at hand. This limitation motivated the research to consider alternative but related approaches for incorporating the aspects of team-performance.

In order to do this and to develop the core C^2D framework and model, we focus on the essential governing factors for team-dynamics relative to performance, as opposed to enforcing particular structures for design-teams. Specifically, we focus the investigation on the factors relating to the formation of design-teams; we do so as the resulting structures of these collaborations and the approaches they take stem theoretically from how these teams assemble. Research from Guimerà, Uzzi, Spiro, and Amaral (2005) supports this approach; their research demonstrates that underlying team assembly mechanisms drive the resulting network structure between collaborators and, as a result, the resulting performance of a collaborative effort as a whole. These findings held true across a variety of tasks and across a range of artistic and scientific efforts. Guimerà et al. (2005) proposes a fundamental three-parameter model of these team assembly mechanisms, consisting of: (1) team size, (2) the fraction of newcomers in new productions, and (3) the tendency of incumbents to repeat previous collaborations. Adopting these parameters as part of the C^2D framework provides a set of parsimonious team-dynamic parameters.

Guimerà et al. (2005) implements these dynamics into a simulation, which starts at time zero with an endless pool of newcomers. With time, these newcomers join the collaboration network as a team. After having joined a team, they transition from newcomers to incumbents. At each time increment or tick, a new team of size n forms and joins the collaborative network. The selection of agents that join these teams arise from the probability (p) of being drawn from the pool of incumbents or its complement probability $(1 - p)$ that equates to the probability of being drawn from the pool of newcomers. In this approach, if an incumbent is drawn, it has a probability (q) of being an existing member of the team. In this sense, the q parameter provides the propensity of a team to repeat collaborations, which, combined when with p provides insight into the relative velocity of turnover on a team. Figure 2.25 provides an overview of how different network structures emerge overtime through the variation of these simple parameters suggested by Guimerà et al. (2005). The characteristics of these emerging network structures vary based on these key parameters of team-formation. This figure utilizes algorithms from the NetLogo team-assembly model from Bakshy and Wilensky (2007). As discussed in the Chapter 4, we adopt the validated elements of this model for the team-assembly procedures in the C^2D model. As shown by Guimerà et al. (2005), these agent-based models allow for the study of emergent network structures resulting from various parameterizations. Additionally, Guimerà et al. (2005) used data from multiple types of collaborative works to validate this modeling approach, ranging from highly creative work in Broadway productions to scientific collaborations in Astronomy. Table 2.6 similarly provides an overview of the differences among these team-assembly preferences from across the multiple work areas studied. Table 2.7 calculates the statistical significance of these findings. Interestingly, the data demonstrates differences between the preferences of the different communities of collaborators, both in regards to the willingness of the group to incorporate newcomers and with respect to their propensity to repeat past collaborations. Figure 2.26 uses this data to provide a look at how these structures emerge and evolve given varying preferences.

From a socio dynamics perspective, Guimerà et al. (2005) posited that teams assemble to incorporate individuals with different ideas, skills, and resources. In this context, teams spur creativity, introducing proven innovations from one domain to the challenges of another domain, and they inspire new insights. For instance, a newcomer brings to bare a new mindset and often-varying background to a team; these newcomers bring to bear a divergent conceptual focus from the normed focus of their more established incumbent teammates. Guimerà et al. (2005) points out that balancing this diversity on a team, between newcomers and the status-quo, represents a challenge given the fact that diversity can also promote conflict and miscommunications between team-members. Possible conflict from bringing new teammates stems from the disruption to the status quo, which upsets the security incumbent teammates enjoy when working and sharing ideas with past collaborators. Conversely, continued collaborations without newcomers and fresh thinking comes at the cost of groupthink and can similarly disadvantage a group. This research similarly assumes that these factors of team dynamics play an essential role in the design process. In the context of design, groupthink can lead the design-team to converge on solutions prematurely, causing the team to fixate on conceptual designs that maybe well understood yet suboptimal to other possibilities in the design landscape.

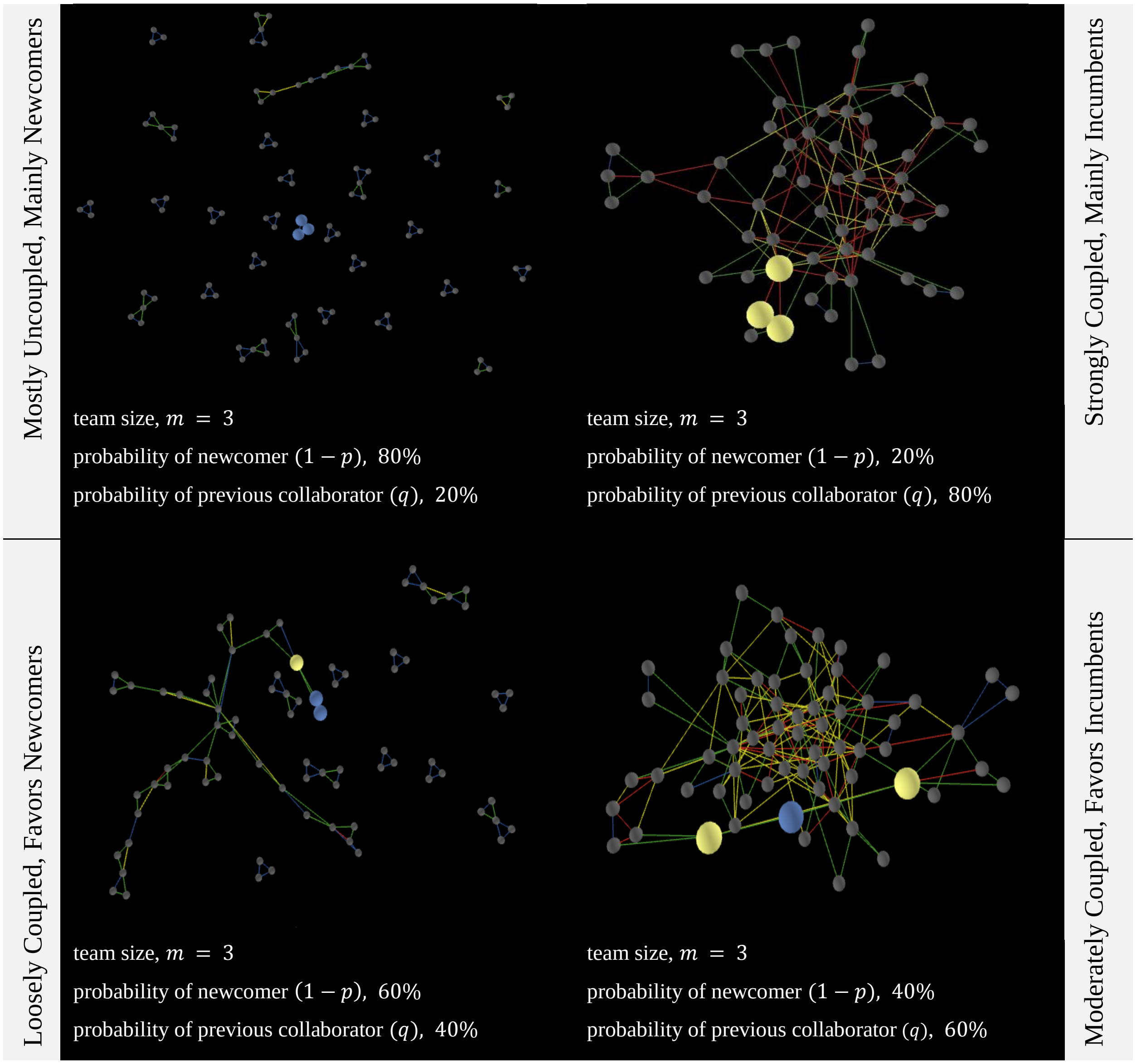


Figure 2.25 Role of Team Assembly Dynamics in the Structuring of Collaboration Networks. We generated this figure using NetLogo code adapted from Bakshy and Wilensky (2007). Each simulation ran 300 ticks and maintained a maximum downtime for agents of 40 ticks (i.e. if they did not collaborate before 40 ticks they left the collaboration). Newcomer-newcomer links seen in blue dominate in the upper left quadrant. Newcomer-incumbent links seen in green tend to dominate in the bottom left quadrant. Incumbent-incumbent links seen in yellow tend to prevail in the bottom right quadrant. Finally, repeat collaborations seen in red tend to prevail in the upper right quadrant. Each quadrant represents different parameterizations of newcomer probabilities and propensities to repeat previous collaborations.

Table 2.6 Summary of Findings from Guimerà et al. (2005). For each field, the total number of productions (i.e. collaborative efforts) and the associated number agents are considered. The table provides extrapolated values from the data for the parameters describing the final size of the networks (N) and the likelihoods that a team would pick a current incumbent (p) and its inclination to repeat previous collaborations (q). Similarly, each point in the (p, q) parameter space considers both the fraction of repeat incumbent-incumbent links (f_r) and the fraction of agents that belong to the largest cluster (S). The table also provides comparisons of the predicted values against the model; this includes predicted values for the fraction S predicted from the model (S_{mod}) and the predicted final size of the model (N_{mod}).

Field	Period	Productions	Agents	$\boldsymbol{p}$	$\boldsymbol{q}$	$\boldsymbol{f_r}$	$\boldsymbol{N}$	$\boldsymbol{N_{mod}}$	$\boldsymbol{S}$	$\boldsymbol{S_{mod}}$
Broadway	1877-1990	2258	4113	0.52	0.77	0.16	428	420	0.70	0.80
Social psychology	1955-2004	16,526	23,029	0.56	0.78	0.22	11,412	14,408	0.68	0.67
Economics	1955-2004	14,870	23,236	0.57	0.73	0.22	9,527	11,172	0.54	0.50
Ecology	1955-2004	26,888	38,609	0.59	0.76	0.23	23,166	26,498	0.75	0.84
Astronomy	1955-2004	30,552	30,192	0.76	0.82	0.39	18,021	22,794	0.92	0.98

Table 2.7 Calculated Pearson Correlations for Team-Assembly Dynamics. We use IBM® SPSS® to analyze the correlations for journal-specific collaborations data. This data examines the identified team assembly factors for specified journals and their impact factor (IF), after Guimerà et al. (2005).

		Agents	$\boldsymbol{p}$	$\boldsymbol{q}$	$\boldsymbol{f_r}$	$\boldsymbol{S}$
Impact Factor	Pearson Correlation	.250	.472**	-.422*	.341	.499**
	Sig. (2-tailed)	.168	.006	.016	.056	.004
	N	32	32	32	32	32

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

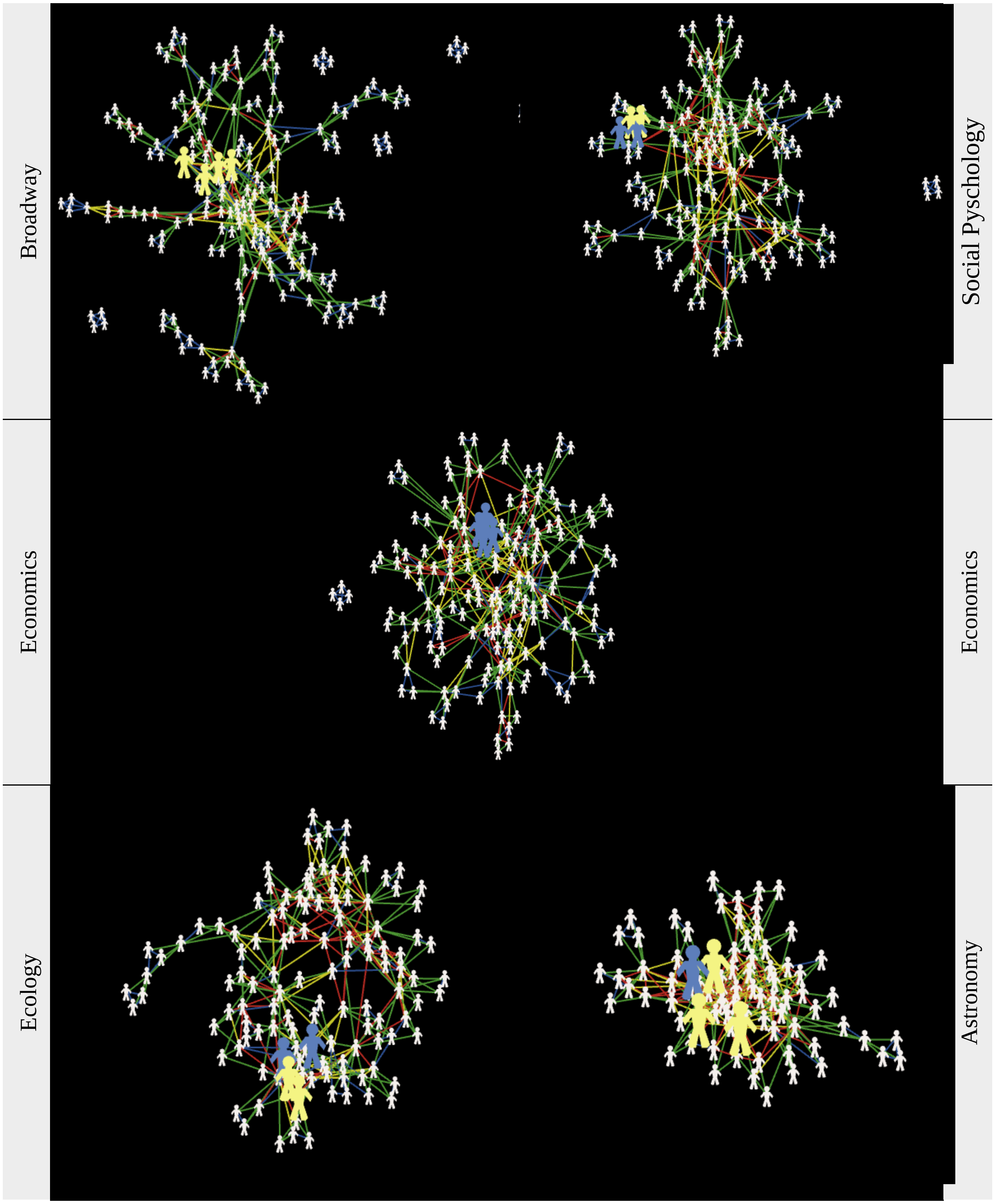


Figure 2.26 Emergent Network Structures after $t = 200\, ticks$ for Team Size $n = 4$. The network structure develop out of the team-formation parameters (i.e. n, p, q, and f_r). We use these parameters from the fields studied by Guimerà et al. (2005). The generation of this figure utilized the C²D model for team-dynamics, *i.e.* the C²D model without the landscape component enabled. These collaboration-network structures are consistent Guimerà et al. (2005) and results using work from Bakshy and Wilensky (2007). This figure provides an initial look ahead for the C²D model.

As the design process represents a strong duality of both creativity, such as that found in artistic fields, and technical rigor, such as that found in the scientific fields, the C^2D model builds upon the collaborative team-assembly framework discussed. The remaining chapters explore the heuristic benefit of this linkage for describing and exploring aspects of design performance. We extend the generalized team model discussed to the earlier discussion of design by connecting the team assembly mechanisms to a design landscape. This approach provides an approach that accounts aspects of both the socio and technical dynamics faced in real-world design scenarios. In the base state of this model, the collaborative network of designers searches the design space through a gradual evolution process towards increasing levels of fitness through the process of natural selection while also continuously adapting its team structure based on the team assembly mechanisms. These fitness values correspond to measures of performance, which provides the final cornerstone of the C^2D framework.

2.5 Performance & Productive Efficiency in Design

Many measures of performance exist in the context of the efficiency measurement literature. However, linkages between these traditional measures of performance and the engineering design domain remain highly unresolved. Triantis (2014) provides an initial bridging of the efficiency measurement literature to several aspects of engineering design. This foundational cornerstone centers on the adoption of performance measurement modelling from the well-explored domain of productive efficiency measurement. Productive efficiency measurement evaluates the use of all resources in a system with regard to their efficiency and system production; this generally includes ensuring the appropriate combinations of inputs to ensure maximum productive efficiency, *i.e.* achieving the maximum level of output possible from a combination of inputs. In particular, Triantis (2004; 2014) focuses on the application of the Data Envelopment Analysis (DEA) model from productive efficiency to concepts in engineering, such as resilience, sustainability, the dynamics of engineering systems, and engineering design among others.

We compare this DEA modelling approach to the concept of *fitness* used in the C^2D approach. Our motivation for this comparison rests in the fact that DEA provides an alternative mathematical optimization schema when considering performance in design. We also pursue this comparison to build on previous work done as part of CAPEM relating CAS production systems to the relationships of general productions systems by extending this analogy to encompass the DAU as one such system (Dougherty, Ambler, and Triantis 2014). Within the context of design, we similarly explore these concepts through the *design landscape*, a framework that allows the research to relate the efficient use of functional requirements $\{\mathrm{FRs}\}$ and design parameters $\{\mathrm{DPs}\}$ to concept of *fitness* as an output.

2.5.1 Related DEA Models

The foundational work by Triantis (2014), relating efficiency performance and engineering, and the work by Dougherty, Ambler, and Triantis (2014), regarding the application of complexity science to performance measurement, provide the theoretical basis for purposes of relating traditional efficiency measurement and performance literature to this research. These works each employed the well-known approach of efficiency analysis known as Data Envelopment Analysis (DEA), a nonparametric method for the estimation of efficient frontiers (Koopman 1951; Farrell 1957; Charnes, Cooper and Rhodes 1978; Banker, Charnes, and Cooper 1984). In addition to its application in economics and its extensions in Operations Research, DEA remains extensible to multiple domains, including engineering, in the form of benchmarks and the creation of "best-practice" frontiers (Triantis 2004; Dougherty, Ambler, and Triantis 2014; Cook, Tone, and Zhu 2014; Triantis 2014). This approach also remains extensible to dynamic and non-linear formulations (Färe, Grosskopf, and Brännlund 1996; Färe and Grosskopf 2000; Vaneman and Triantis 2003; Vaneman and Triantis 2007). This recent extension of DEA to include dynamics, known as Dynamic Productive Efficiency Modeling (DPEM) together with its standard DEA antecedent, help to inform this research by providing the building blocks of productive efficiency analysis that will enable the extension of DEA into the world of engineering design, specifically engineering design in the context of complex adaptive systems thinking.

The standard DEA model provides the approach to compute relative efficiencies among firms, organizations, or systems in which there are multiple inputs or multiple outputs, and in which, it is desirable and possible to aggregate these inputs or outputs into a single measure of relative efficiency (Charnes, Cooper, and Rhodes 1978). This form of analysis allows for the comparison of performance among individual decision-making units (DMUs). Firms, organizations, or systems can each represent these DMU entities. In the context of C^2D, the individual designers represent the DMUs of interest, *i.e.* each designer makes decisions about its adaptions and movements on the *design landscape*.

DEA provides an approach for identifying the most efficient DMUs among a population of similar DMUs; through this approach, DEA allows for the creation of benchmark comparisons. These benchmarks inform policy makers and can help to guide future decision-making. The objective of DEA is to optimize the efficiency of each DMU first and foremost and as a consequence the entire population of DMUs; this objective provides each DMU a means of determining policies for becoming more efficient. In the context and analogy of C^2D, this allows for the comparison of performance for individual designers as well as a method to improve overall design performance vis-à-vis improving the overall performance of the population of designers through different design management strategies. Implicit to these statements rests the concept of an objective function. In value-centric engineering design efforts, this objective function can represent a value function (Collopy and Hollingsworth 2011).[17]

In the Charnes-Cooper-Rhodes (CCR) DEA model from 1978, the efficiency of a system depends on the relative proportion of virtual inputs to virtual outputs, *i.e.* weighted inputs (v_i) and weighted outputs (u_r). This leads to an optimization objective built around finding optimal input and output weights for n DMUs. The inputs include (X), a (m x n) matrix, and, similarly, its outputs include (Y), a (s x n) matrix. This concept of efficiency for a DMU_o follows from (Charnes, Cooper, and Rhodes 1978; Cooper, Seiford, and Tone 2007):

$$\theta = \frac{virtual\ input}{virtiual\ output} = \frac{v_1 x_{1_o} + \cdots + v_m x_{m_o}}{u_1 y_{1_o} + \cdots + u_s y_{s_o}} \tag{2.20}$$

Where:

θ = measure of productive efficiency

u_s = weight given to output s, v_m = weight given to input m

Given data, the CCR model measures the relative efficiency (θ) of each DMU_o once, and, as a result, requires n optimizations for the whole population. This model constructs an efficient frontier around the benchmarks established around the highest performing DMUs, as shown

[17] In the C^2D framework, we adopt the more general objective of improving *fitness*, which for purposes of this research remains synonymous to the general conceptualization of value from Collopy and Hollingsworth (2011); however, this exploration remains the subject of future research collaboration.

subsequently. This frontier establishes the theoretical optimal ratios of input sand outputs across a production possibility space, *i.e.* the space defining all possible combinations of inputs and outputs. In other words, the DMUs with the best relative efficiency of inputs to outputs from the overall population of DMUs form a benchmark of efficiency performance. This benchmark also represents a reference set of continuing relative efficiency values (θ) of one. The efficiency (θ^*) values for the remainder of the inefficient DMUs range between zero and less than one. In essence, this model establishes performance rankings between the individual DMUs. Using a linear program (LP) to optimize efficiency, the formulation follows (Charnes, Cooper, and Rhodes 1978; Cooper, Seiford, and Tone 2007):

$$\max_{\mu,v} \theta = \mu_1 y_{1_o} + \cdots + \mu_s y_{s_o} \tag{2.21}$$

Subject to:

$$v_1 x_{1_o} + \cdots + v_m x_{m_o} = 1$$

$$\mu_1 y_{1_j} + \cdots + \mu_s y_{s_j} \leq v_1 x_{1_j} + \cdots + v_m x_{m_j}$$

$$v_1, v_2, \ldots, v_m \geq 0, \quad \mu_1, \mu_2, \ldots, \mu_m \geq 0$$

Where:

θ, objective function and measure of productive efficiency

μ_s, weight given to output s

v_m, weight given to input m

$j = 1, \ldots, n$ DMUs

The combinations of possible input and output relationship establish a set of all possible production activities. More formally, the input and output vectors $(\underline{x}_j, \underline{y}_j)$ for $j = 1, \ldots, n$ belongs to the production possibility space P. Additionally, given an activity $(\underline{x}, \underline{y})$ belonging to P, then the activity $(t\underline{x}, t\underline{y})$ also belongs to P for any positive scalar t. This is the result of the CCR model assumption of constant returns to scale (CRS), *i.e.* the increase of all inputs by t *results* in a constant proportional increase to outputs by t. Finally, for any activity $(\underline{x}, \underline{y})$ in P, any semi positive sequence of activity $(\underline{\overline{x}}, \underline{\overline{y}})$ with $\underline{\overline{x}} \geq \underline{x}$ and $\underline{\overline{y}} \geq \underline{y}$ is similarly included in P. As a result, the set of feasible activities making the production possibility space follows (Charnes, Cooper, and Rhodes 1978; Cooper, Seiford, and Tone 2007):

$$P = \{(x, y) |\ x \ \geq X\,\lambda,\ \ y\ \leq Y\,\lambda,\ \ \lambda\ \geq 0\,\} \tag{2.22}$$

Where:

λ , a semi-positive multiplier vector in $\Re^n$

$x \in \Re^m$, semipositive input

$y \in \Re^n$, semipositive output

$X = [x_j]$

$Y = [y_j]$

(x_j, y_j) = observed activities $(j = 1, \ldots, n)$ belong to the production

This CCR model can also similarly represent equation (2.21) in vector-matrix notation (Cooper, Seiford, and Tone 2007):

$$\max_{\underline{v},\underline{u}} \underline{u}\ \underline{y}_o \tag{2.23}$$

Subject to:

$$\underline{v}\ \underline{x}_o = 1$$

$$\underline{u}Y - \underline{v}X \leq 0$$

$$\underline{v} \geq 0, \qquad \underline{u} \geq 0$$

Where:

$\underline{u}$ = row vector of output multipliers, $\underline{v}$ = row vector of input multipliers

In these preceding formulations, the CCR model objective is to maximize the ratio of "virtual outputs" to "virtual inputs" for DMU$_o$, the DMU under evaluation, by finding optimal weights for the inputs and outputs. By understanding the optimal relationship between inputs and outputs, these weights enable policy makers to minimize inputs while producing a given output level for a population of DMUs. However, this research focuses on the maximization of performance through the analogy of *fitness* values. In other words, instead of using formulations that lower inputs to achieve efficiency, the research approach more readily aligns to DEA formulations that increase outputs or in our case fitness values to achieve efficiency. To do this we depart from input-orientated formulations of CCR to focus on the output-orientated formulations of CCR. This formulation uses the dual problem of equation (2.23) and transforms it into the following dual linear program in equation (2.24) with an output-orientation model (Charnes, Cooper, and Rhodes

1978; Cooper, Seiford, and Tone 2007). This model attempts to maximize outputs while using no more than the observed amount of inputs.

$$\max_{\eta,\underline{\mu}} \eta \tag{2.24}$$

Subject to:

$$x_o - X\underline{\mu} \geq 0, \qquad \eta\underline{y}_o - Y\underline{\mu} \leq 0\,, \qquad \underline{\mu} \geq 0$$

Where:

η, objective function to increase output efficiency and weights for outputs

$\underline{\mu}$, multiplier vector

However, as mentioned earlier this model enforces constant returns to scale (CRS). This assumption does not necessarily lend itself to the most apt analogy of the rugged fitness landscape employed in the C^2D framework; in fact, the CRS assumption, as shown subsequently, results in the simple landscape of an efficient plane. However, different models such as the Banker-Charnes-Cooper (BCC) model from 1984 do not require CRS and allow for variable return to scales (VRS). The BCC model constructs its production frontiers through the construction of a convex hull surrounding the existing DMUs. The output oriented LP for the BCC envelopment model follows (Banker, Charnes, and Cooper 1984; Cooper, Seiford, and Tone 2007):

$$\max_{\eta_B,\ \lambda} \eta_B \tag{2.25}$$

Subject to:

$$X\lambda \leq x_o\ , \quad \eta_B y_o - Y\lambda \leq 0,$$
$$e\lambda = \sum\nolimits_{j=1}^{n} \lambda_j = 1\,, \quad \lambda \geq 0$$

Where:

η_B, objective function and measure of productive efficiency

λ, weights given to the DMUs

e, row vector with all elements unity, *i.e.* equal to 1

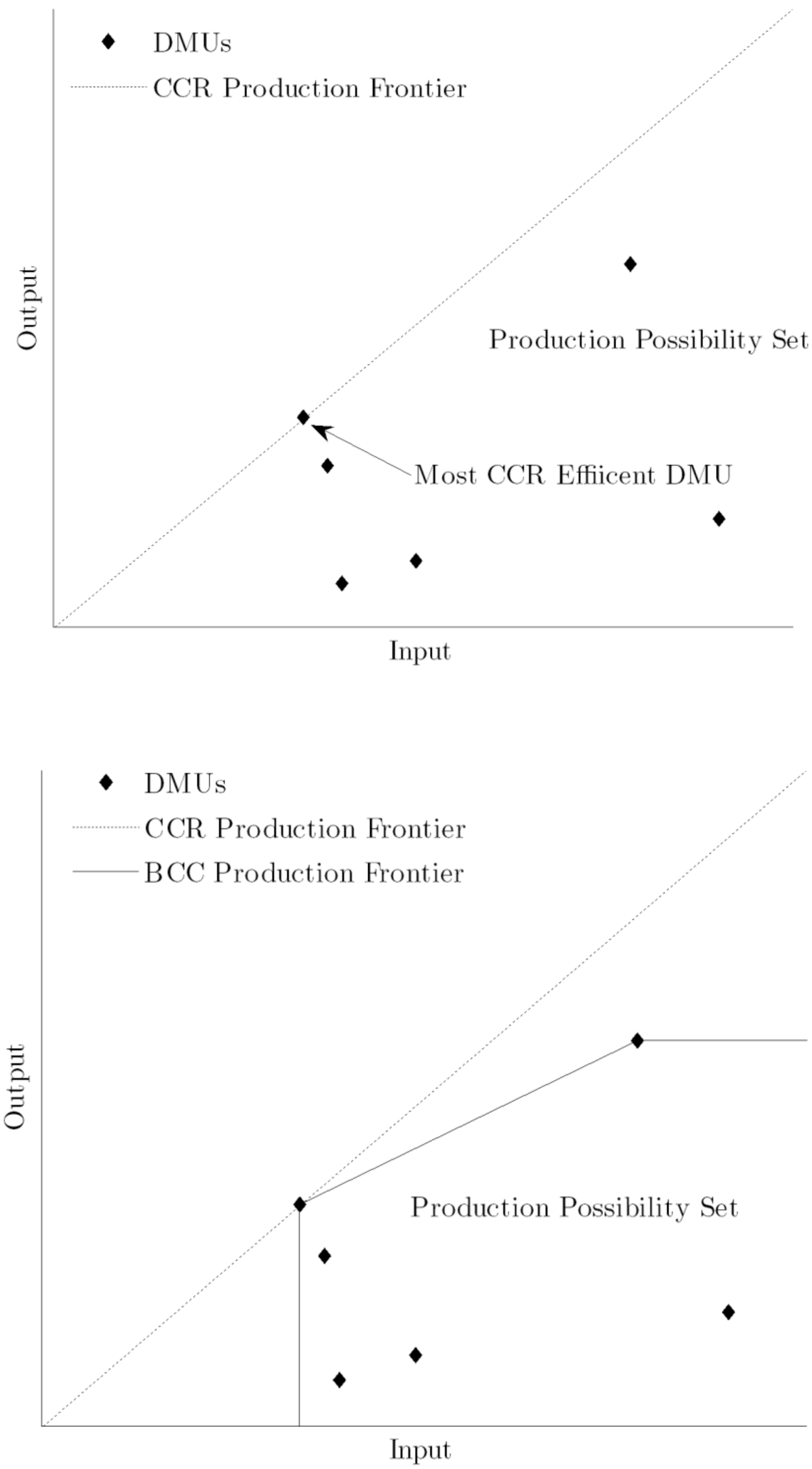


Figure 2.27 Comparison of the Efficient and Production Frontiers from the CCR Model (top) and BCC Model (bottom)

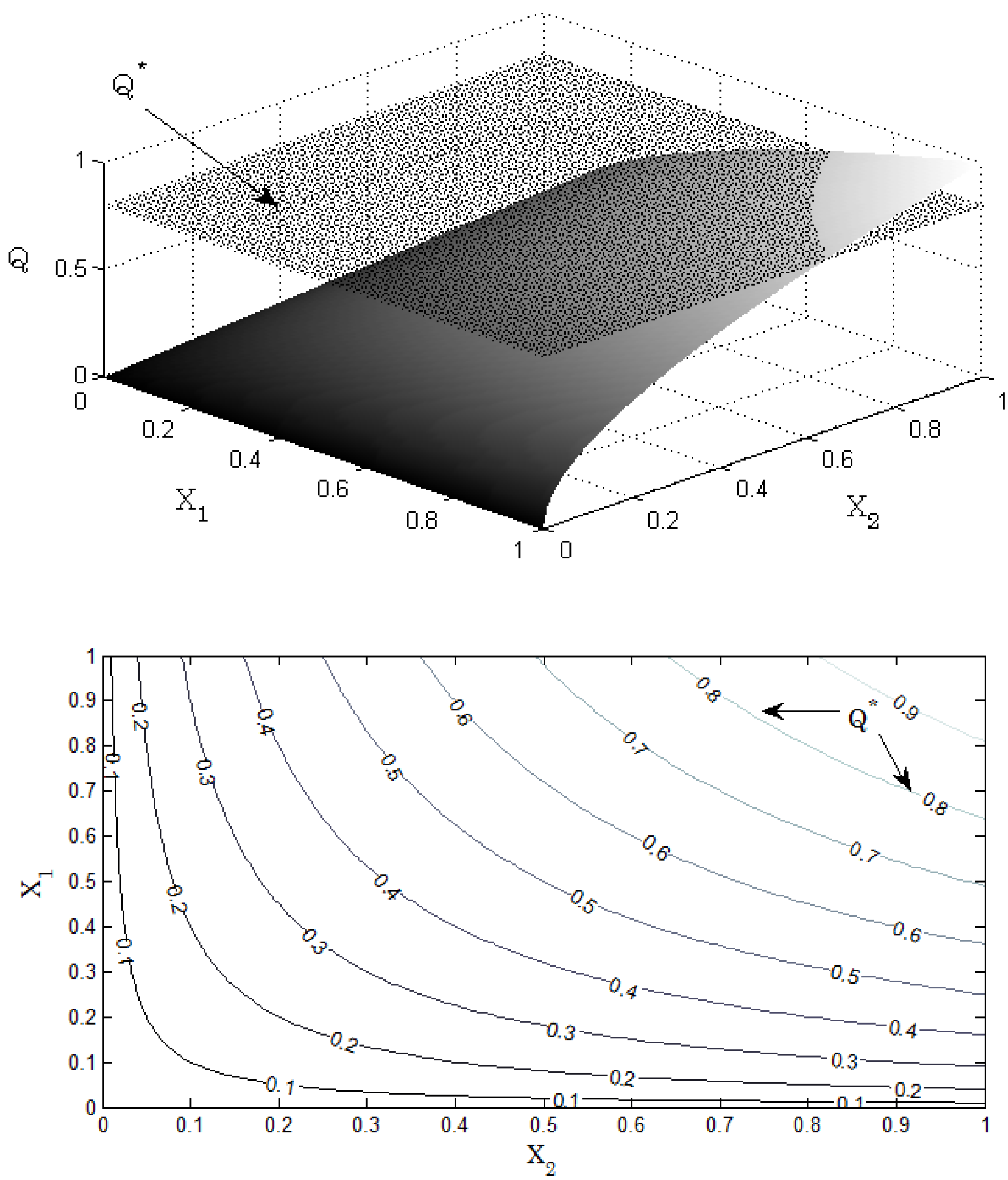


Figure 2.28 Representations of the Efficient Frontier as a Landscape. This figure demonstrates the bisection of a desired production level with a theoretical productive landscape as generating the efficient frontier, analogous to the contour lines of the figure (bottom). The above figure relates the theoretical production (Q) from two inputs X_1 and X_2 using a Cobb-Douglas parametric production equation $Q = {X_1}^{0.5}\,{X_2}^{0.5}$, while incorporating the desired level of production of $Q^* = 0.8$ through a rectangular bisecting plane. Given enough DMU observations, the efficient frontier as seen in Figure 2.27 represents the intersection of this theoretical Q and Q^*. Variations in the constructions between this theoretical representation of the production frontier and those derived from DEA models stem from modelling specific assumptions and from limitations in the number of DMU observations. In a dynamic context, the underlying theoretical production may change with time, and, as a result, so too may the efficient frontier. Appendix E includes the MATLAB code used in producing this Figure.

The BCC formulation differs from the CCR model only in the adjunction of the condition $e\lambda = 1$ and comes closer to matching the general concepts of this research. As a result, the set of feasible activities making the BCC production possibility space follows (Banker, Charnes, and Cooper 1984; Cooper, Seiford, and Tone 2007):

$$P = \{(x, y)|\ x \ \geq X\,\lambda,\ \ y\ \leq Y\,\lambda, e\lambda = 1, \lambda\ \geq 0\,\} \qquad (2.26)$$

Where:

λ , a semi-positive multiplier vector in $\Re^n$,

X = $[x_j] \in \Re^{m \times n}$

Y = $[y_j] \in \Re^{s \times n}$, semipositive output

(x_j, y_j) = observed activities $(j = 1, \ldots, n)$ belong to DMU_j

However, exploring the *design landscape* from the C^2D model as an appropriate analogue to productive landscapes requires modifying the discussed models or exploring additional models of productive efficiency. The convexity restriction $e\lambda = 1, \lambda_j = 1, \lambda_j \geq 0, \forall j$ imposed by the BCC model limits efficiency landscapes to smooth convex hull relationships, such as the one shown in the above figure. Although these restrictions can be relaxed by allowing $e\lambda \geq 1$, resulting in a non-decreasing return to scale case, or by bounding it to $0 \leq e\lambda \leq 1$, resulting in a non-increasing return to scale case, other models allow more flexibility in their accounting of nonconvex relationships. We explore two key considerations in the literature, the free-disposal hull model and methods for handling congestion, before explicitly discussing the underpinning axioms of production as they relate to engineering design.

The Free Disposal Hull (FDH) model from Deprins, Simar, and Tulkens (1984) bases its efficiency evaluations strictly on known observations. The boundary of these observations and their connections represent the hull, defined as the "smallest set" that encloses the production possibility space, and follows as (Deprins, Simar, and Tulkens 1984; Cooper, Seiford, and Tone 2007):

$$P_{FDH} = \{(x, y)|\ x\ \geq x_j,\ \ y\ \leq y_j, x, y\ \geq 0, j = 1, \ldots, n\,\} \qquad (2.27)$$

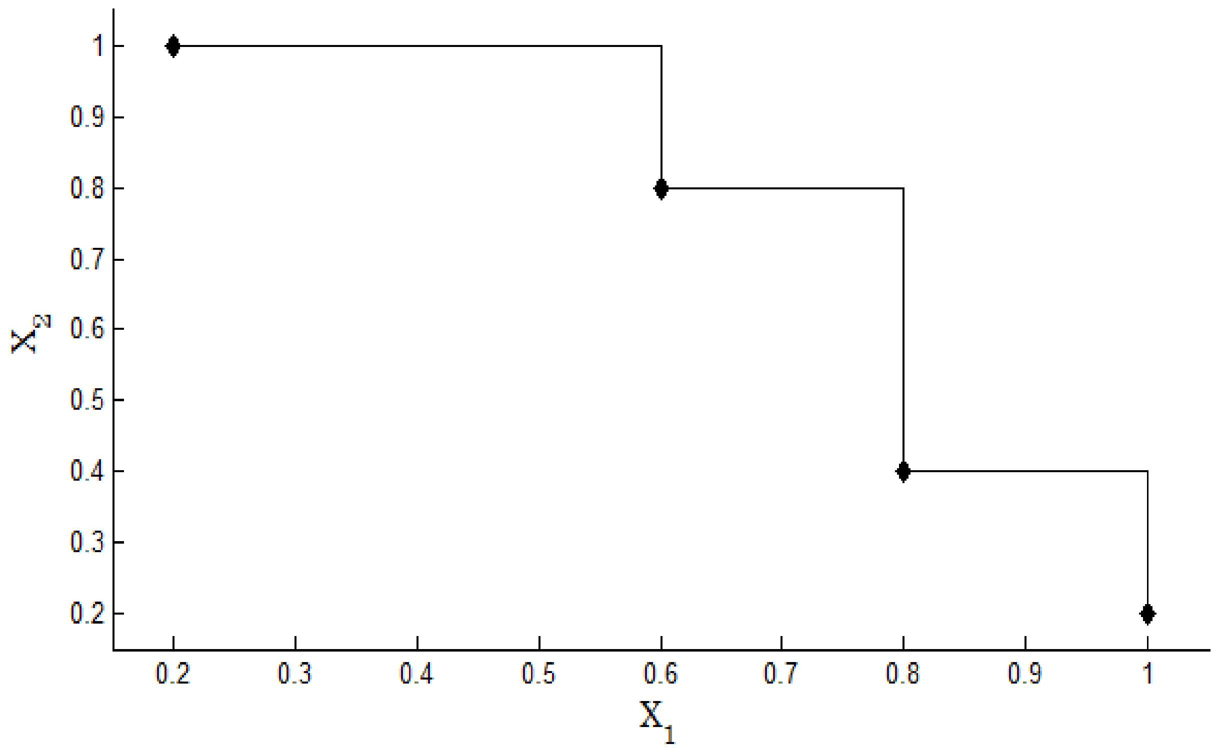


Figure 2.29 Example of a Two Input (x_1 and x_2) and One Output (y = 1) FDH Output Model

This FDH model distinguishes itself from traditional forms of DEA by relaxing its convexity requirement. The general construction of the FDH production frontier requires the elimination of all dominated points; the following mixed integer programming formulation removes these dominated points (Cooper, Seiford, and Tone 2007):

$$\min \theta \tag{2.28}$$

Subject to:

$$\theta x_o - X\underline{\lambda} \geq 0$$

$$y_o - Y\underline{\lambda} \leq 0$$

$$e\underline{\lambda} = \sum_{j=1}^{n} \lambda_j = 1, \quad \lambda_j \in \{0,1\}$$

The FDH estimator measures the efficiency of a point relative to the boundary of the Free Disposal Hull of the sample set. For the output-oriented case, optimization of the estimator follows from the integer linear program (Daraio and Simar 2007):

$$Z_{FDH} = \max\ \lambda \tag{2.29}$$

Subject to:

$$\lambda y_o \leq \sum_{j=1}^{n} \lambda_j Y_j$$

$$x_o \geq \sum_{j=1}^{n} \lambda_j X_j$$

$$\sum_{j=1}^{n} \lambda_j Y_j = 1$$

$$\lambda_j \in \{0,1\},\ j = 1, \dots, n$$

The *design landscape*, and its foundation as a NK fitness landscape discussed earlier in Section 2.3.2, parallel the bivalent construction, *i.e.* 0 or 1, of the FDH model landscape. For example, the NK fitness landscape depends on a binary construction as seen in equation (2.18), and, as seen in Chapter 3, the construction of the *design landscape* similarly captures interactions in terms of bivalent weights in the design matrix $[A]$ as $\lambda_{ij} \in \{0,1\}$. However, this model similarly shares the implicit assumption that an increase to one or more inputs improves outputs, regardless of scale. This assumption does not hold in some conceptual applications of the analogy of production landscapes to the varied ruggedness of fitness landscapes. The concept of congestion parallels the concepts of Pareto optimality and its application in engineering, where the improvement to one design parameter, in the context of this research, may hurt the fitness contribution of another design parameter. In the literature regarding DEA models, this concept relates to the occurrence of "congestion," where, similarly, an increase in one or more inputs may actually cause the worsening of one or more outputs (Cooper, Seiford, and Tone 2007). The cited example from the literate of "congestion" stems the phenomenon where, for example, adding more miners might actually degrade the mining outputs (Cooper, Seiford, and Tone 2007). This occurrence represents non-monotonicity, *i.e.* the production frontier increases and decreases with inputs.

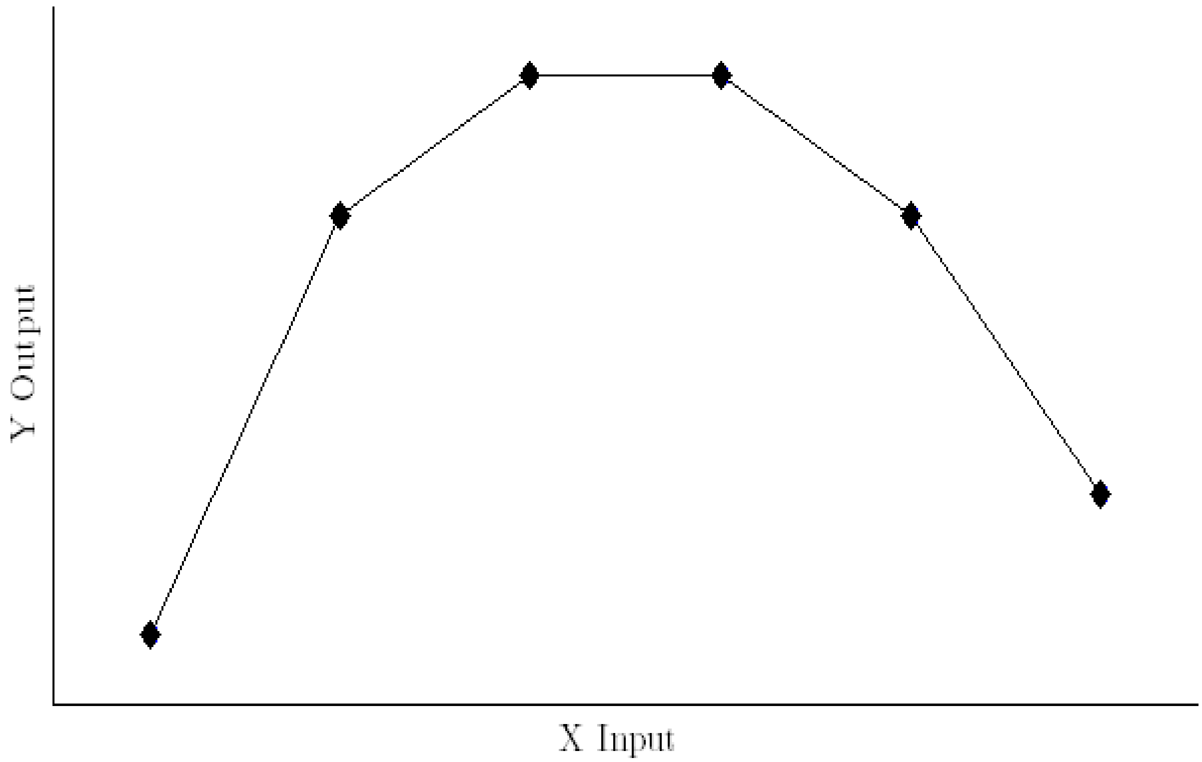


Figure 2.30 Congestion in Design. The figure demonstrates that increased inputs can actually cause outputs to worsen; this event depicts the phenomenon of "congestion" from economics. Conversely, decreases to one or more inputs without worsening one or more outputs similarly represents a form of input congestion. Measures of congestion utilize both radial measures of efficiency, *i.e.* comparison measures from the origin of chord lengths, and non-radial measures, *e.g.* the use of slacks.

In order to incorporate congestion and non-monotonicity in the construction of a comparative landscape for design, we build on the literature by suggesting the construction of a landscape using the intersection of two Free Disposal Hull models. We build on the concept of creating an output additive FDH^T estimator as done by Abbasi, Jahanshahloo, and Rostamy-Malkhlifeh (2014). This estimator establishes the production possibility space starting from the right, *i.e.* with decreasing inputs in order to maintain disposability and study congestion. This adaptation for the production possibility space varies from equation (2.27) only in the sign of the input inequality:

$$P_{FDH^T} = \{(x, y) | \; x \; \leq x_j, \;\; y \; \leq y_j, x, y \; \geq 0, j = 1, \dots, n \} \tag{2.30}$$

This construction allows for the exploration of congestion. This FDH^T estimator similarly measures the efficiency of a point relative to the boundary of the Free Disposal Hull of the sample set as in equation (2.29). For the output-oriented case, optimization of the estimator follows from the integer linear program (Daraio and Simar 2007; Abbasi, Jahanshahloo, and Rostamy-Malkhlifeh 2014):

$$Z_{FDH^T} = \max \lambda \tag{2.31}$$

Subject to:

$$\lambda y_o \leq \sum_{j=1}^{n} \lambda_j Y_j$$

$$x_o \leq \sum_{j=1}^{n} \lambda_j X_j$$

$$\sum_{j=1}^{n} \lambda_j Y_j = 1$$

$$\lambda_j \in \{0,1\}, j = 1, \dots, n$$

Although left in part to continued investigation, the *design landscape* construction represents a strong analogy to special construction of the FDH model. As discussed the *design landscape* uses points, randomly assigned along a bit-string as specified from its NK construction. If we consider each of these points as a DMU, in the sense that they specify the production possibility space, we can then begin to establish a comparison between both constructions. Using only the observed output levels, *i.e.* fitness values from the NK construction, we can establish a FDH production possibility space; however, the *design landscape* makes no assumptions similar to congestion.

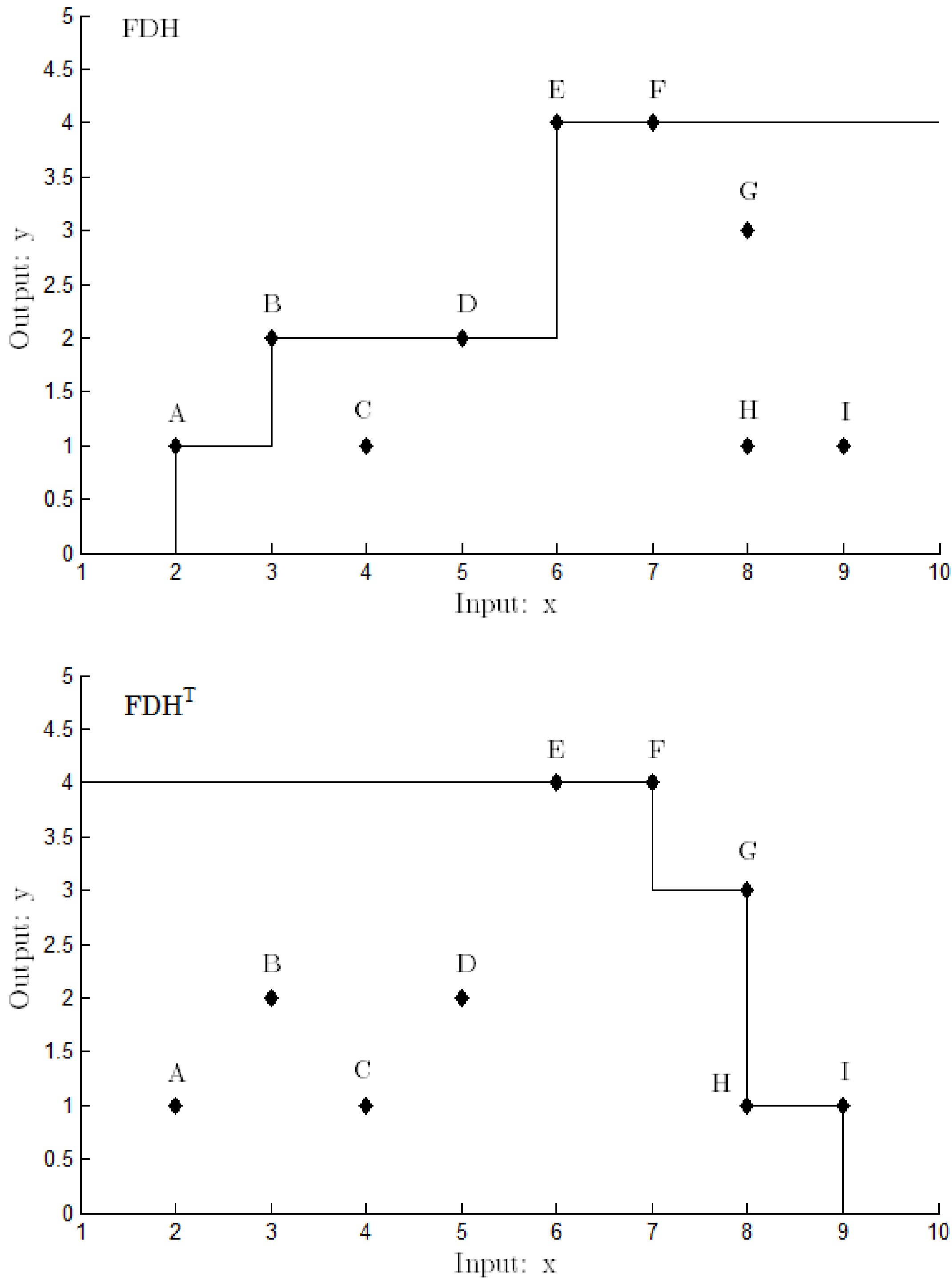


Figure 2.31 Efficient Frontier of the FDH and FDH^T Model. These surfaces are staircase functions based on the observation of dominated DMUs. The production possibility space established by the FDH model relaxes input disposability assumptions, and the FDH^T model incorporates strong congestion, i.e. a reduction in all inputs warrants an increase to outputs.

This leads us to the adoption of the following theoretical production possibility space from equation (2.27) and equation (2.30):

$$P_{NK} = P_{FDH} \cap P_{FDH^T} \tag{2.32}$$

The construction of the optimization problem similarly follows as a two-step linear integer program from equation (2.29) and equation (2.31):

$$Z_{NK} = \min(Z_{FDH}, Z_{FDH^T}) \tag{2.33}$$

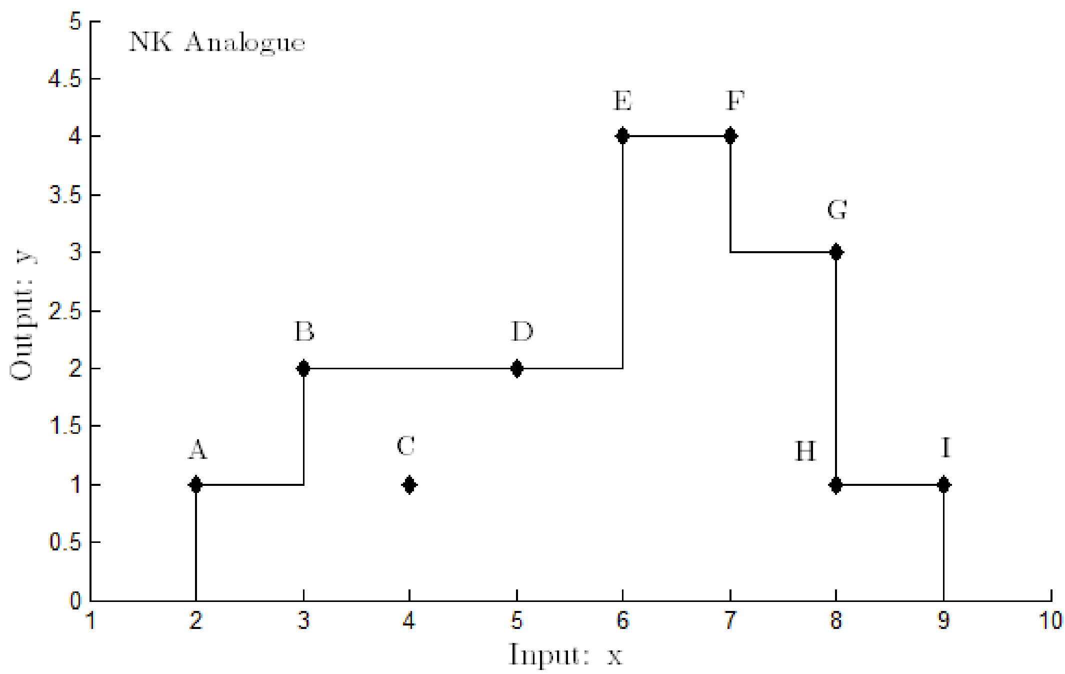
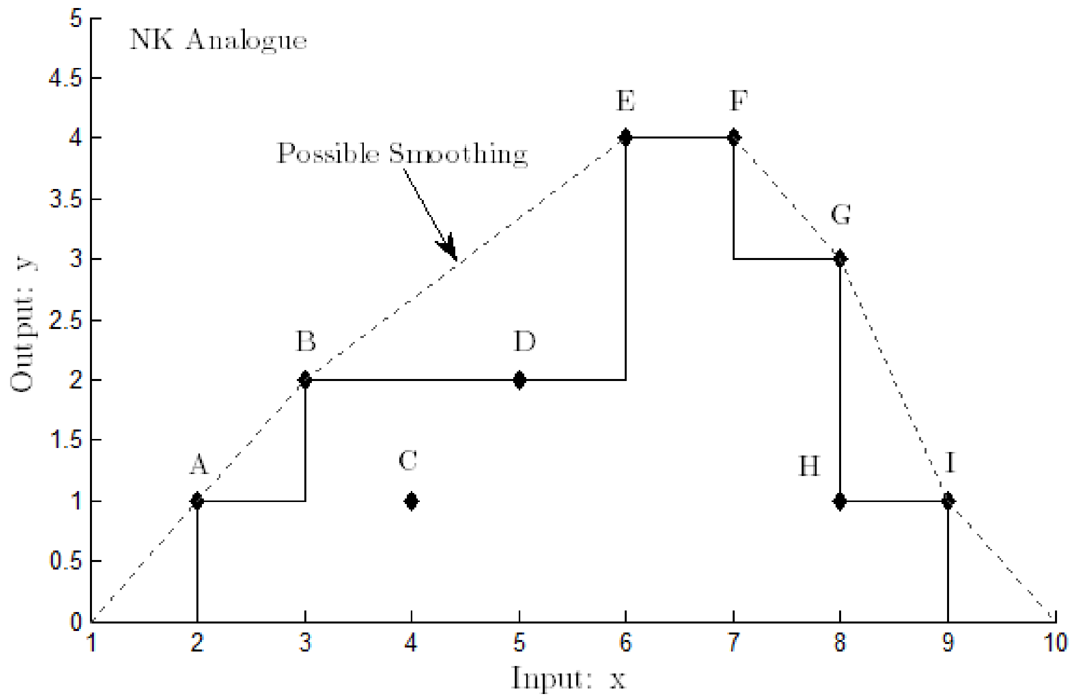


Figure 2.32 Representation of the Production Possibility Space for a Theoretical NK Model. The output values in the conceptualization of the *design landscape* correspond to design fitness values. The inputs to these models correspond to individual design elements of a design matrix $[a_{ij}]$. In the above example, there are nine DMUs or nine design elements; as we enforce square matrices for an ideal design, this corresponds to a three by three-size design matrix. By definition, this matrix relates three functional requirements to three design parameters. Each of the design elements, *i.e.* DMU A through DMU I, receive a randomly assigned fitness value based on the level of interaction between other design elements. If the design matrix remains perfectly adherent to the independence of requirements axiom of design, then the epistatic relationships given by K equals zero. As the number of simulations approach infinity, the landscape in this case approximates a smooth landscape resembling Mt. Fujiyama as shown earlier and discussed by Kauffman (1971). However, its ruggedness varies depending on the interactivity level K. Tying this concept to the genotype analogy from Wright (1932), each of these DMUs act as possible alleles connected by mutagenic pathways.



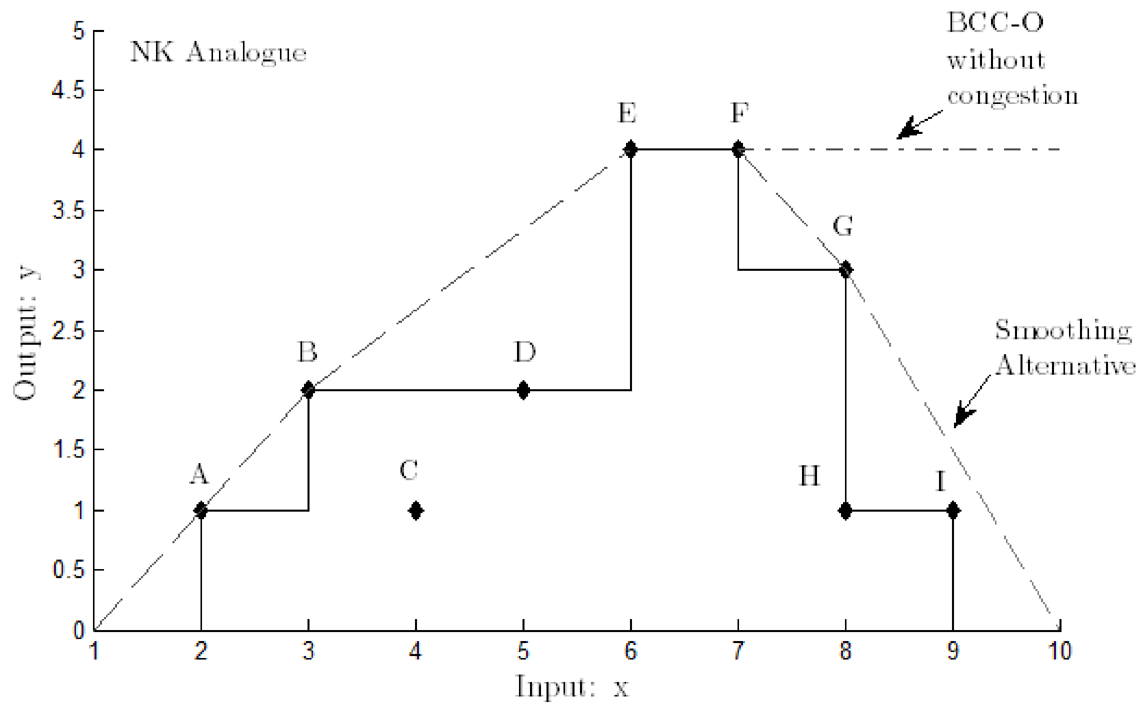


Figure 2.33 Smoothing the Landscape. In the C[2]D framework, we allow for smoothing to occur in the model at the discretion of the modeler. As a result, the step function nature of the production possibility space P_{NK} can also then approximate characteristics of other models. This smoothing concept has implications for future research, as well as adaptions to more robust forms of DEA models. One implementation of this smoothing, in this options the model examines connects nearest neighbors (top). However, a similar intersection approach for BCC models can provide this smoothing function (bottom).

2.5.1.1 Axioms of production

The "theory of the firm" underpins the theoretical DEA models discussed (Hendersen and Quandt 1971). This theory includes the axioms of production, which concisely articulate fundamental observed patterns of production. These axioms remain foundational building blocks within DEA. The CAS representation of efficiency, demonstrated with CAPEM by Dougherty, Ambler, and Triantis (2014), initially demonstrated general conformance to these axioms. The C^2D model similarly adheres to these axioms, with the relaxation of the convexity and free disposability restrictions as initially discussed. The axioms of production are:

- Axiom 1 - No Outputs: it must be possible for the production system to produce zero outputs even with the presence or addition of inputs;

- Axiom 2 - No Free Lunch: production of outputs cannot occur in the absence of inputs;

- Axiom 3 - Free Disposability: a DMU must always be able to produce the same level of output, even if the levels of input vary;

- Axiom 4 – Scarcity: the level of producible outputs remains limited or bounded, *i.e.* finite inputs can only yield finite outputs;

- Axiom 5 – Closedness: it is only possible to produce positive real numbered amounts of outputs with only positive real numbered amounts of input; and,

- Axiom 6 – Convexity: if a series of inputs x_i can produce y, then any weighted combination of x_i can produce y

As discussed, the DEA linear programming models conform to basic physical laws and known economic patterns of production. These patterns form the basis of the discussed "axioms of production." Traditional DEA representations and models of productive efficiency must conform to these axioms or have specific stated reasons for the relaxation of an axiom. We summarize how the C^2D model both adheres to and departs from these axioms using both the general axioms of production and the dynamic formulation of these axioms as recently defined by (Vaneman and Triantis 2003).

These axioms, including their more detailed components, follow:

Axiom 1(a), the inactivity axiom, states that it must always be possible to produce no outputs:

The C[2]D framework allows designers to explore less fit design options, including designs with no fitness. This can occur either through inefficiency, shown as in the 3D landscape as traveling under the fitness landscape at the bottom, in the case of zero, or through the exploration of ineffective design (i.e. valleys in the fitness landscape). Enforcing this axiom in a modelling context first requires establishing a coordinate system to enforce the boundaries of a production space from which the disposal of production may occur, such as a Cartesian coordinate system. In the case of C[2]D, the vertical axis of the 3D model or the color gradient equivalent in 2D represent the output bound by the productivity space P for all elements of the input space.

Dynamic Axiom 1(a). $0_t \in P(x_{t-t_o};\ y_{t_d-t_o}), \forall(x_{t-t_o};\ y_{t-t_o}) \in \mathfrak{R}_+^N$

According to this axiom, absent the addition of inputs into the system during the time horizon $[t_o, t_d]$ the system comes to or remains at rest or in a state of static equilibrium. This follows from the concept of Newtonian mechanics, *i.e.* an object at rest remains at rest unless acted upon by an outside force and absent continued momentum, which requires inputs in the case of the axiom, the system returns to a state of rest.

To conform to this axiom the C[2]D framework includes the possibility of a designer exploring a design concept with zero fitness or, through analogy, a productive efficiency of zero for an increment of time.

Axiom 1(b), the no free lunch axiom, states that production of outputs requires inputs:

This axiom, known as the "No Free Lunch" axiom from Färe and Primont (1994), states that it is not possible to produce outputs or stay at static equilibrium at time t, in the absence of inputs during the time interval $[t_o, t]$.

Dynamic Axiom 1(*b*). $y_t \notin P\left(x_{t-t_o};\ y_{t_d-t_o}\right) = 0\ for\ y_t > 0$

The C[2]D framework ensures that absent the basis of a design, *i.e.* the input basis for the system, the design landscape has no performing points. Given this approach, the designers will not find any performing locations during any periods that lacks a design approach, *i.e.* zero fitness and through analogy zero output. We define the design approach, the inputs, as both an understanding of the functional requirements and design parameters.

Axiom 2(a), the weak input disposability axiom, states proportional increase to inputs will not decrease outputs:

This axiom states that a proportional increases to all inputs will not decrease outputs. However, in the case of multiple inputs and outputs, if increase to inputs do not occur in a proportionally basis outputs may decrease (Färe and Grosskopf 1996).

Dynamic Axiom 2(a). $y_t \in P\left(x_{t-t_o};\, y_{t_d-t_o}\right) \wedge\, \lambda \geq 1 \rightarrow\, y_t\, \in P\left(\lambda\, x_{t-t_o};\, y_{t_d-t_o}\right)$

The DPEM dynamic axiom further expands upon this concept to ensure that if inputs were to increase proportionally during the time horizon $[t_o, t]$ then outputs will never decrease at the corresponding time, t. Conversely, without proportionally increase to inputs during the time horizon $[t_o, t]$ then outputs may decrease at the corresponding time, t.

The C^{2}D framework, if given a convex surface, for example from a convex production or value function, can simulate the productive efficiency with the assumption of weak input disposability. However, we relax this assumption to include the possibility of congestion. Recall the previous discussion of Pareto optimality from engineering, if for some configurations of design a certain combination of design elements were to require Pareto optimality any increase, including proportional, may limit the fitness of a design configuration.

Axiom 2(b), the strong input disposability, states any increase to inputs will not decrease outputs:

This axiom concerns the occurrence of excessive input slack and states that if any input increases, whether proportional (including weak proportionality) or not, outputs will not decrease (Färe and Grosskopf 1996). In a dynamic context, changes in inputs x_{t-to} during the time horizon $[t_o, t]$, whether proportional or not, do not change output y_t at the corresponding time period t.

Dynamic Axiom 2(b). $y_t \in P\left(\check{x}_{t-t_o}; y_{t_d-t_o}\right) \wedge x_{t-t_o} \geq \check{x}_{t-t_o} \rightarrow y_t \in P\left(x_{t-t_o}; y_{t_d-t_o}\right)$

The DPEM dynamic similarly ensures that if any inputs were to increase during the time horizon $[t_o, t]$ then outputs will never decrease at the corresponding time, t. Conversely, without the addition of inputs during the time horizon $[t_o, t]$ then outputs may decrease at the corresponding time, t.

As before, the C[2]D framework, if given a convex production or value function, can simulate the productive efficiency with the assumption of strong input disposability. However, as before we relax this assumption to include the possibility of congestion. Recall the previous discussion of Pareto optimality from engineering, if for some configurations of design a certain combination of design elements were to require Pareto optimality any increase, including proportional, may limit the fitness of a design configuration.

Axiom 3(a), the weak output disposability, allows the proportional reduction of outputs:

This axiom states that a proportional reduction of outputs remains possible (Färe and Primont 1994). Output slack represent undesirable output or, colloquially, economic waste. This axiom allows for a reduction in the waste through a proportional reduction in desired. Thus if output y_t is produced by input x_{t-to}, a weighted output φy_t can also be produced by input x_{t-to}, when $\varphi y_t < y_t$.

Dynamic Axiom 3(a). $y_t \in P\left(x_{t-t_o}; y_{t_d-t_o}\right) \wedge 0 \le \varphi \le 1 \rightarrow \varphi y_t \in P\left(x_{t-t_o}; y_{t_d-t_o}\right)$

This dynamic formulation ensures that the model can eliminate outputs proportionally. The C[2]D framework allows for the reduction of all outputs whether proportional or otherwise. In this example of the design framework, designers are free to adopt a less fit design. In addition, in the sense of the construction of the design matrix elements, the algorithm allows for the stochastic generation of any value, providing structural output disposability in the model.

Axiom 3(b), the strong or free output disposability, allows disposal of outputs without cost:

This axiom states that outputs can be disposed of without cost. The cause of this condition may be an inefficient production process that generates waste, whose removal would entail no consequence (Färe and Grosskopf 1996).

Dynamic Axiom 3(b) $y_t \in P\left(x_{t-t_o}; y_{t_d-t_o}\right) \wedge \check{y}_t \le y_t \rightarrow \check{y}_t \in P\left(x_{t-t_o}; y_{t_d-t_o}\right)$

In a dynamic system, production processes during the interval $[t_o, t]$ may yield outputs whose disposal would carry no cost; this axiom imposes the condition that this output remain exogenous to the production system of interest, in order to prevent feedbacks into the system. The C^2D framework allows for the reduction of all outputs whether proportional or otherwise. In this example of the design framework, designers are free to abandon a design concept all together in favor of an improved design concept without adversely affecting the overall fitness.

Axiom 4, the scarcity axiom states that the output set remains bound in some manner:

This axiom states that finite amounts of input can only yield finite amounts of output (Färe and Primont 1994). In a dynamic environment, the inputs also remain bounded within the time domain. Thus, bounded resources within $[t_o, t]$ can only yield finite outputs at corresponding time, t.

Dynamic Axiom 4. $\forall\, x_{t-t_o} \in \Re^N_+,\ y_t \in P\left(x_{t-t_o}; y_{t_d-t_o}\right)$ is a bounded set

The dynamic axiom enforces the same approach to ensure that the set of possible outputs remain bound in some manner. When, for example, the ends of the efficient frontier do not include x or y intercepts the analyst can assume the horizontal or vertical line that includes these points. As shown in the construction of the FDH model, the space of the C^2D model remains bounded according to the production possibility space.

Axiom 5, the closedness axiom, states that the output set is finite:

This axiom states that if a given input can produce every sequence of an output vector Y, then the associated input vector X can produce the output (Färe and Primont 1994).

Dynamic Axiom 5. $\forall\, x_{t-t_o} \in \Re^N_+,\ y_t \in P\left(x_{t-t_o}; y_{t-t_o}\right)$ is a closed set

The scarcity and closedness axioms ensure that the output space function *P(x)* is a compact set, a finite set in space that contains all possible limit points. In the dynamical environment, if the inputs X at time $t_o - t$ can produce every sequence of vectors Y at time t, then x_{t-to} can produce y_t. In the C^2D model, the establishment of the design matrix establishes a closed set. Additionally, the implementation of the NK construction enforces this closedness.

Axiom 6, the convexity axiom, states that productions possibilities remain convex set:

The weighted combination yields a line segment that joins the two points (Hillier and Lieberman 1995). The extreme points and the line segment must all be contained in the solution space. Thus if x_i and $\breve{x}_i$ are both a series of inputs that can produce y, then any weighted combination of x_i and

$\breve{x}_i$ can produce y. In a dynamic sense, x_i and $\breve{x}_i$ can be inputs during different times within the time interval $[t_o, t]$ as long as their respective outputs share a common time period t.

Dynamic Axiom 6. $\forall\, x_{t-t_o} \in S(y_t) \in \Re_+^N \;\; if \;\; 0 \leq \lambda \leq 1 \rightarrow$
$\lambda\big(x_{t-t_o}; y_{t-t_o}\big) + (1-\lambda)\big(\breve{x}_{t-t_o}; y_{t_d-t_o}\big) \in S(y_t)$

The dynamic formulation follows from the normal axiom, enforcing convexity at each time t. In the C^2D model all DMUs, *i.e.* designers, remain contained within both the input and output spaces of the problem analyzed; however, these spaces do not adhere to convexity. As discussed as part of disposability, these landscapes include aspects of non-monotonicity that require the relaxation of the convexity requirement (as well as free disposability).

2.5.1.2 Note on measures of efficiency

Technical efficiency (TE) reflects the current ability for a DMU to produce an output for a given input. We have discussed this concept of technical efficiency tangentially as it related to DEA models; however, the relationship between fitness and these measures requires further explanation, especially as to the typical derivations and types of efficiency. A technically efficient DMU uses its inputs to achieve a maximum level of output (or to a minimum level of input as governed by the optimization model); these efficient units operate by definition on the production frontier. A technically inefficient unit operates below this production frontier, thus it is not optimally using its inputs to produce outputs (Farrell 1957; Coelli, Rao, and Battese 1998). The efficiencies of all DMUs undergo a process of normalization, typically with respect to the most efficient DMU, to enable a direct comparison between units. The most efficient DMUs become the standard and benchmarks used by inefficient DMUs. While this research focuses largely on the effectiveness of teams and on their technical efficiency, for completeness it is necessary to point out that standard DEA provides the means of making comparisons in the form of not only technical efficiency, but also in terms of allocative efficiencies and overall efficiency. TE characterizes the physical efficiency of transforming inputs into outputs, while allocative efficiency characterizes the economic or price efficiency associated with transforming inputs into outputs (Farrell, 1957). The C^2D framework constructs its landscape based on the efficient frontier and landscape, and focuses on technical efficiency. Figure 2.34 provides an example from Vaneman and Triantis (2004) for completeness.

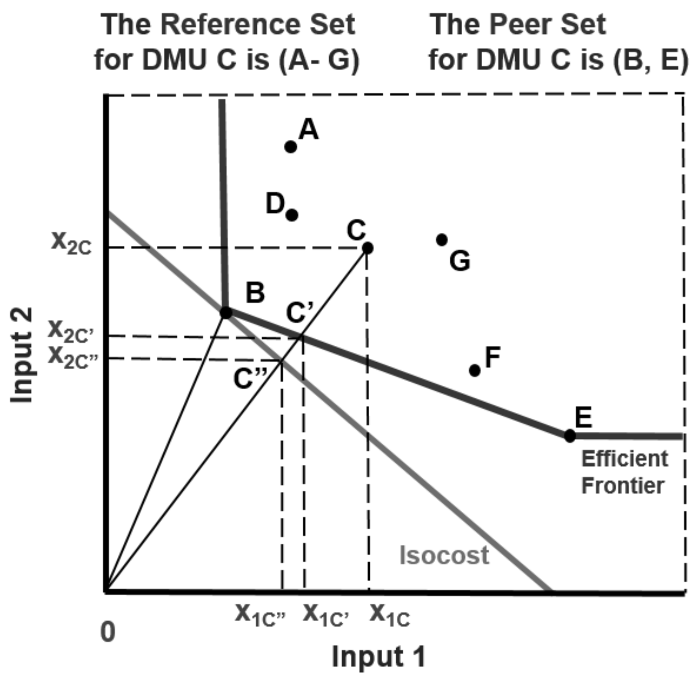


Figure 2.34 Input Minimization Problem. Problem derived from Vaneman and Triantis (2004) to highlight technical and allocative efficiency concepts. We reproduce this figure with permission from the authors. Technical efficiency (TE), allocative efficiency (AE), and overall productive efficiency (OPE) represent the comparison of the points C-to-C' and C-to-C'' with respect to the origin. In this example, this comparison yields the following relationships from Farrell (1957):

$$TE = \overline{OC}/\overline{OC'} \qquad AE = \overline{OC}/\overline{OC''} \qquad OPE = TE \text{ x } AE$$

The value for $\overline{Ox}$ represent the chord length from the origin to a point x on the plane. This approach allows for the analysis of efficiency by comparing the measured values with respect to an optimal technical and optimal cost point indicated by point B above. A technically efficient (TE) DMU lies on the efficient frontier. An allocatively efficient (AE) DMU lies at the isocost line. The most efficient DMU (*i.e.* the DMU(s) with the greatest OPE) lies at the intersection of the efficient frontier and the isocost lines. This provides an example where the goal centers on minimization of inputs; however, the inverse construct applies for handling output-oriented measures. In the case of the *design landscape*, the point from which efficiency is measured represents the point $O = (x_1, x_2, z) = (0,0,0)$. In this context solutions further away from the origin, the point where the design-team starts its exploration, although they have higher fitness values may represent less efficient solutions as it takes the design-team longer to find them. Although we limit the current scope of testing for this research to focus primarily on the effectiveness and technical efficiency of design-teams navigating along the design landscape, the C^{2}D framework also allows for movements in the z-axis that are decoupled from the design landscape. When this axis is left unrestricted, the C^{2}D model provides for future testing of efficiency measurement concepts beyond the scope of this work. This work includes measures of technical efficiency; however, the relaxation of convexity restrictions have important repercussions for its measurement. For example, design activities that represent feasible and efficient points on the design landscape may remain clearly less ideal then similar combinations of inputs and outputs elsewhere on the landscape. As a result, search times, ceteris paribus, for the design-team underpin the fundamental relationships of design-team efficiency.

The literature also provides some initial thoughts on the application of DEA to engineering, engineering design, and engineering management applications (Triantis 2004; Triantis, Vaneman, and Pasupathy 2008; Keller 2012; Dougherty, Ambler, and Triantis 2014). However, as Triantis (2014) highlights, engineers themselves have not extensively adopted efficiency measurement paradigms to evaluate the performance of engineered systems, which in part, as previously discussed, motivated this research. In fact, many of the models employed by engineers remain divergent to the concepts and constraints imposed by the outlined production axioms, such as convexity. Nevertheless, there exists a symmetry between the optimization approaches employed in DEA and several engineering applications, especially given the relaxation of convexity axiom of production; based on the author's experience similar optimization routines exist across multiple engineering applications (e.g. thermo-fluid applications, finite element analysis, power optimization systems for spacecraft). As the C^2D model focuses both on the design space, *i.e.* the design matrix that relates how design parameters can meet functional requirements, and on the design process, *i.e.* how designers composing teams search the design space, we explore definitions of these concepts from Triantis (2014):

$$P_{\substack{Design\\Space}} = \{f(x,y): x \in \Re_+^N,\ \ y \in \Re_+^M: \text{resource x can lead to design outcome y}\} \tag{2.34}$$

$$P_{\substack{Design\\Process}} = \{f(x,y): x \in \Re_+^N,\ \ y \in \Re_+^M: \text{process x can lead to design outcome y}\} \tag{2.35}$$

We adapt these definitions to the C^2D framework as follows:

$$P_{\substack{Design\\Space}} = \{f(\{FRs\},\{DPs\},f_d): \{FRs\},\{DPs\} \in \Re_+^N,\ f_d \in \Re_+^M: \{FRs\} \wedge \{DPs\} \rightarrow f_d\} \tag{2.36}$$

$$P_{\substack{Design\\Process}} = \{f\left(M_S, M_p, f_t\right): M_S, M_p \in \Re_+^N,\ f_t \in \Re_+^M: M_S \wedge\ M_p \rightarrow f_t\} \tag{2.37}$$

We use the same definitions throughout the work; however, we introduce the design process in equation (2.37) as a function to achieve design-team fitness (f_t) using strategies (M_S) and model parameters (M_p), including parameters describing team-formation. Similarly, we discuss the design fitness (f_d) as a function of $\{FRs\}$ and $\{DPs\}$ in equation (2.36). Although we focus only on the conceptual design process, this possibility space statement when expanded to the overall design process must also incorporate the $\{CAs\}$ and $\{PVs\}$ as additional inputs. In Chapter 3, we discuss design performance, as well as the overall construction of the C^2D framework, as an intersection of this design space and design process.

3

C^2D Associative Inferences

"I think the next century will be the century of complexity."
Stephen W. Hawking
San Jose Mercury News, 2000

What makes engineering design complex or rather any system complex? After having explored this question in detail in the preceding chapter, we encapsulate its core characteristic as the whole of an entity exceeding the sum of its parts. *Emergence*. In other words, the individual and additive cause and effect relationships from constituent elements do not fully explain the resultant behaviors of the overall system at different scales of inquiry. As shown in the earlier chapters, both engineering artefacts and the design process alike clearly exhibit characteristics consistent with its classification as a complex system. Almost all modern design efforts concerning large-scale systems require an extensive number of interactions between design participants, many of whom maintain individual design preferences for a particular subsystem and, in the case of a lead designer, control over the design decisions for a particular design element. Speaking from personal observation, the creation of an advanced engineered artefact, such as a space system, often includes the participation of several thousand design engineers and managers working in parallel with designers focusing on individual design elements and with managers and system engineers focusing on a subset of elements comprising a subsystem or system. When engaged in the process of design these participants coordinate their actions and exploration of the design space through a set of design processes and organizational constructs. We can conceive of these design processes and organizational constructs as constraints and rules imposed on a design objective to maximize design fitness.

The high degree of interactions that occur within the engineering design process reveals the highly collaborative nature of the design process. *Res ipsa loquitur*. We structure rules to capture the highly collaborative interactions that occur within the engineering design process. We choose collaboration as the fundamental dynamic of interest as these collaborative processes entail time-consuming and expensive processes to manage, especially in the presence of complexity or, more specifically, the presence of strong interdependencies of design elements. These interdependences exacerbate the difficulties encountered in the design process as they link the decision of one decision-making unit, e.g. the designer, to a subset of interdependent decision-making units, e.g. other design engineers responsible for different design elements. Understanding this collaborative nature of design and the resulting linkages and relationships between designers underscores this work and the creation of an analytical framework, which we capture through a set of rules that, more specifically as addressed in Chapter 2, govern the nature of how collaborations form.

In addition to the expense and time-consuming nature of current approaches for collaborative design, current approaches also focus on mitigating complexity through the incremental improvement of previously successful designs, often coming at the cost of innovation and unincorporated downstream lifecycle considerations (Klein, Sayama, Faratin, and Bar-Yam 2003). We structure a framework to capture the behaviors of these collaborating designers as they attempt to improve their fitness by using a theoretical *design landscape*, an analogue of the NK landscape, and a set of collaboration centric rules for the designers. We create this framework to provide a platform to analyze beneficial parameterizations of collaboration that may improve the current processes of design.

We structure this chapter around the elements of this *Complex Adaptive Performance Evaluation Method for Collaborative Design* (C^2D) framework to explore what design means in its context as a collaborative and complex adaptive socio-technical system. We structure this discussion of the C^2D framework in terms of the following aspects:

- Clarifying the approach;
- Establishing the design landscape;
- Collaboration dynamics of the design-team;
- Connecting the design process and design landscape in a unified framework; and,
- Benefits of the C^2D analytical framework

3.1 The C²D Approach

The objective of this chapter is to detail the C²D CAS-based approach for the analysis of engineering design-team performance. In this approach, we examine the performance of the design-team as the result of individual designers, the decision-making units (DMUs), involved in collaborative engineering design efforts. We define the DMU reference set of interest for the framework as the set of designers working together collaboratively on an engineering design effort of interest. We limit this initial research approach to the case where all designers exploring the *design landscape* belong to an individual collaborative team. However, the framework described remains extensible for the future inclusion of multiple coevolving design-teams.[18] We assume that the objective of any analyzed design process centers on achieving a specified design fitness (f_d^*), which in the C²D framework requires an equivalent team fitness (f_t) value to satisfy the design objective. The framework treats the designer as an individual agent of an overall collaborative CAS ecosystem engaged in the process of achieving a design goal while simultaneously recognizing the autonomous, goal-oriented, non-deterministic, and non-linear nature of decision making for these individual designers. We adopt the notion from Dougherty, Ambler, and Triantis (2014) of using an agent-based DMU (ADMU) to represent designers in an agent-based modelling approach. The resulting modelling framework connects both the exploration space of design to the exploration process required in the design process through the introduction of agent-based designers engaged in the search of a *design landscape*. These connections allow the research to explore relationships most likely to improve the design of new products and engineered systems. Figure 3.1 provides an overview of the casual relationships explored in the context of the C²D framework and model where the italicized elements represents key parameters or measured variables.

[18] Ongoing research strongly supports the extension of C²D to include simultaneous and independent design-teams (i.e. multiple DMU reference sets), often with competing goals. These competing design-teams, similar to the discussed C²D model, require singular final design selections on a *design landscape* through a set of simple design rules imposed on the model. This logical extension adopts the notion of coevolution on a coupled fitness landscape, as done in the Sendero NK Coevolving Species ($NKCS$) model (Kauffman 1995; Padget et al. 2011). Padget et al. (2011) explains this concept of coevolution in terms of the movements of one species (i.e. a DMU reference set) affecting the fitness characteristics and resulting fitness of other linked species (i.e. other DMU reference sets) in the ecosystem (e.g. a Production Possibility Space (PPS) such as the one defined by the *design landscape*). In the C²D extension, this coevolution occurs between different design-teams comprising multiple DMU references sets.

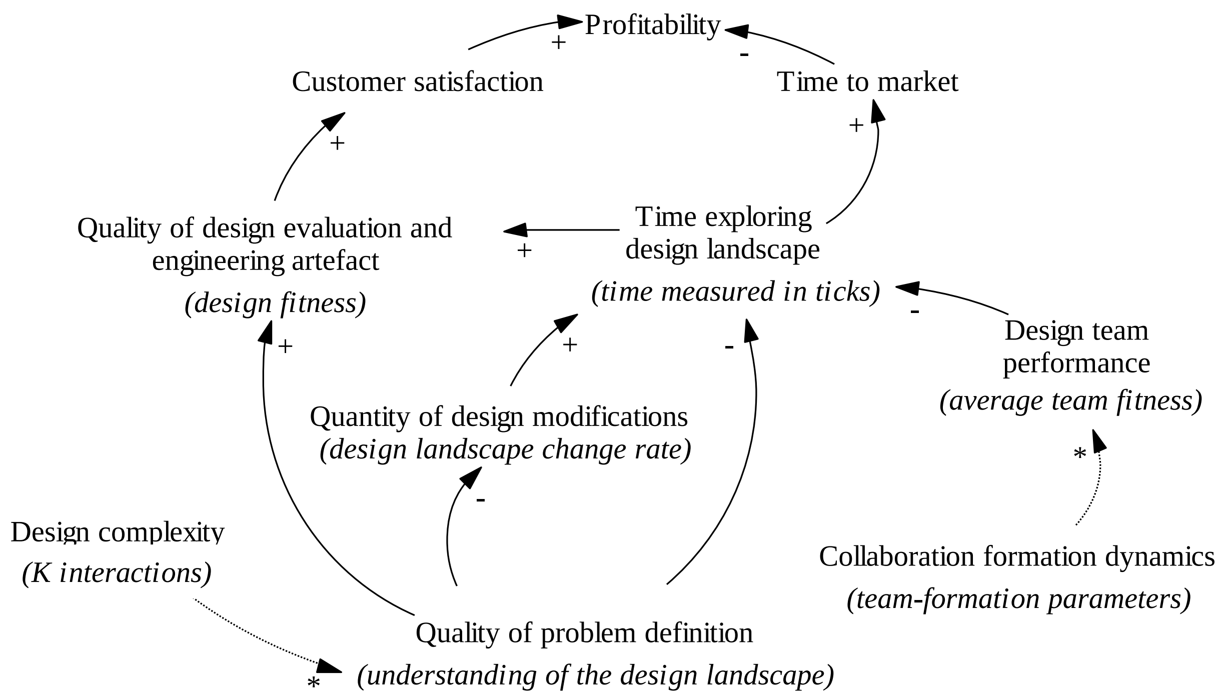


Figure 3.1 Causal Relationships between Design Complexity, Design-Team Performance, and Time to Market. The causal relationships of key C[2]D relationships to engineering design; the primary relationships under inspection for this research focus on the linkages denoted with asterisks: K interactions and team-formation parameters. The number of interactions K measures the interdependencies between the elements of design $[A_{ij}]$ of the design matrix $[A]$ as previously discussed in Chapter 2. These interdependencies between the elements of design theoretically drive uncertainty into the problem definition, in turn degrading the problem definition and the likelihood of achieving design objectives as seen in the definition of complexity from Suh (1990). In the proposed framework, we focus on the relationships between complexity and the quality of the problem definition vis-à-vie the smoothness of the *design landscape* (S^*) variable. This variable S^* follows from a derived relationship to the K variable discussed by Kauffman (1993) as discussed in Section 3.2. Theoretically, we can also relate the abstract smoothness (S^*) from the landscape to test the concepts of uncertainty from Suh (1990) by relating the discussed common range from design ($A_{CR} = A_{DR} \cap A_{SR}$) to the design range ($A_{CR}/A_{DR}$). Hypothetically, this relationship to S^* serves as a proxy measurement for the probability of an engineering design effort to meet its objective (cf. equation (2.4), Section 2.1.2). We test this assumption through Hypothesis 12 of the research (cf. Section 1.2) in Chapter 5. Similarly, we explore the other primary linkage through a set of team-formation parameters based on research originally performed by Guimerà et al. (2005). These team-formation parameters include the probability of a team incorporating a newcomer (p), the propensity of team members to repeat collaborations (q), newly assembled team size added to the collaboration (n), the maximum allowable downtime before a team member leaves a collaboration (mdt), and, as amended in in the C[2]D framework, the maximum allowable diversity of a team member (m). These team-formation parameters, as well as the number of interdependencies, provide the main parameters for experimentation (shown in dashed causal lines). The proposed framework allows for exploration of these relationships and provides an analyst the ability to test varying complexity-mitigation design management strategies.

In this chapter, we build upon a conceptual bridge developed by Dougherty, Ambler, and Triantis (2014) for linking the concepts of CAS thinking as defined by Holland (1998) and the notions of productive efficiency analysis, as defined by DEA, described by Cooper, Seiford, and Tone (2007). We build on this theoretical foundation in order to provide the discussed linkages between the design space and the design process; these linkages enable the overall C^2D analytical framework to evaluate and explore possible strategies for improving the efficiency and effectiveness of design-teams. We distinguish effectiveness from efficiency in the context of this framework as the ability of the designer-artefact-user (DAU) to achieve the design fitness objective f_d^*, as opposed to how well the DAU make these decisions. We explore efficiency in the context of technical efficiency and the time required to achieve fitness objectives.[19] In order to provide concreteness to the framework we explore each of these major aspects of the framework individually and then provide a unifying context that embodies the mapping of causal relationships provided above.

3.2 Technology and the Design Landscape Representation

Use of fitness landscapes provide a platform to explore the dynamic evolutionary processes inherent to natural systems; this platform, in so doing so, also provides a broad and powerful metaphor for understanding the optimization processes of complex systems in general. We use the concept of a fitness landscape to create a bridge between the complexity within the technological elements of design and the performance characteristic of fitness through the creation of a *design landscape*. We construct this *design landscape* in the C^2D model through the adoption of a random field model, in particular the NK model from Kauffman and Weinberger (1989).[20] This approach

[19] We adopt the definition of technical efficiency as previously discussed in Chapter 2, as the occurrence where producing the same level of output cannot occur with fewer inputs, *i.e.* the maximum production of outputs from a given set of inputs (Coelli and Battese 2005). We explore the relationships of efficiency under multiple parameterizations of the collaboration formation dynamics over several experiments using the associated C^2D model (cf. Chapter 4 and Chapter 5). Primarily these efficiency comparisons examine the final team fitness values measured by f_t^* and the search time t_s resulting from the design process with respect to the design process inputs used in the model. These inputs include the size of the design-team given by $dim\{D\}$, number of the functional requirements $dim\{FRs\}$ in the design space $[A]$, and the level of complexity (i.e. interdependencies in $[A]$) given by K and as implemented in the model (i.e. the multiplicative inverse of the landscape smoothness S^*). We use traditional BCC-DEA analysis discussed in Chapter 2 and a meta-analysis where different configurations of design-team formation parameters represent individual DMUs to derive insights as discussed as part of Chapter 6.

[20] The structure of a fitness landscape has the mathematical structure of a N-dimensional hypercube (i.e. polytope of size$N$) with 2^N corners; in the events some combinations of relationships are not viable or absent, the construction the fitness landscape represents a sub-graph of this hypercube (Visser and Krug 2014).

depends on the probabilistic assignment of fitness values to the interactions between design elements.

As described in Chapter 2, the *design landscape* provides a varying terrain structure based on the amount the degree of interactions between design elements; the results terrains vary from relatively flat constructions to highly rugged terrains. As a result, highly interdependent design structures result in a *design landscape* consisting of a range of mountains with local peaks (points from which all paths are downhill) and valleys (points from which all paths lead uphill). Landscapes consisting of multiple local peaks surrounded by deep valleys represent a type of landscape notionally classified as rugged. Implicit in this conceptualization of fitness is the concept of natural selection. As a population gradually evolves through a series of genetic changes, they increase their relative fitness; as a result, the fitter populations produce an increasing amount of offspring capable of similarly reproducing comparatively faster than other populations, thus gradually driving populations over time toward a state of a higher fitness. We build on this concept by introducing the notion of the engineering design-team as an evolving population, whose movements along the *design landscape* similarly represent adaptations of the design-team to the current configuration of design elements. In order to create this framework we define its core components:

- Revisiting the design matrix, design pleiotropy and polygeny;
- Design fitness, an axiomatic comparison;
- Establishing the *design landscape*;
- Complexity in the *design landscape,* formalisms; and,
- Examples of design applications

3.2.1 Design Pleiotropy and Polygeny

This research uses the design matrix as the basis for applying the notions from evolutionary biology as discussed by Wright (1932), in particular the use of fitness landscapes, to engineering design. These fitness landscapes in their original instantiation aid the visualization and study of the evolutionary processes acting on a biological entity. This construct enables analysis of how a biological entity (e.g. population, genus, species, protein, gene, nucleotide) searches a complex space for increased fitness through the processes of evolution. We adapt this concept, along with the notions of modelling epistatic interactions from Kauffman and Weinberger (1989), to visualize how a designer or design-team, the biological entity analogue, search the design space. In particular, we study the influence of interdependencies in the design space using the related NK landscape discussed by Kauffman and Weinberger (1989) in their exploration of epistatic interactions (cf. Chapter 2, Section 2.3.2). To enable this analogy and the research approach, we use the design matrix $[A]$ discussed previously as part of the axiomatic approach to design discussion (cf. Chapter 2, Section 2.1.2). This matrix quickly enables dependency tracing between the technical elements of a design as off-diagonal elements in its matrix by definition represent interdependencies between different functional requirements and design parameters. These off-diagonal elements A_{ij} represent the edges between vertices i and j from algebraic graph theory (Godsil and Gordon 2001). We subsequently address these vertices in terms of the functional requirements $\{FRs\}$, this construct allows us to capture the influence one requirement may exert on another. This exertion, *i.e.* the interdependencies between functional requirements vis-à-vie design parameters $\{DPs\}$, parallels the notion of epistatic interactions in genetics where the effect of one gene may depend on the presence of one or more particular modifying genes. In this context, the N functional requirements provide the genetic makeup of a design and the design parameters represent the f fitness components of that design, *i.e.* the elements that give rise to the fitness of the design.[21] In the biological context, a fitness component (e.g. viability, mating success) can contribute to differences in the total fitness of individuals, *i.e.* influencing their ability to leave behind offspring. In design, the key physical characteristics of a design, defined by the design parameters, similarly contributes to the total fitness of a design by determining the ability of a design to satisfy the functional requirements.

We explore this concept of interdependencies and interactions within design by paralleling the biological construct of pleiotropy and polygeny, as seen in Table 3.1. In its biological application, pleiotropy and polygeny help to relate the influence between fitness components of a biological entity (roughly any biological trait likely to increase it probability to reproduce) and its genetic components. In this construct, we assume that each functional requirement guides the decision-making of at least one design parameter.

[21] In order to satisfy the independence axiom of design the number of $\{DPs\}$ given by f must remain greater than or equal to the N number of $\{FRs\}$ in a design; ideally, according to the axiomatic rules of design, the N number of $\{FRs\}$ should equal f number of $\{DPs\}$ in its construction (Suh 1990).

Table 3.1 The Design Matrix as a Function of Design Pleiotropy and Polygeny[22]

Design Parameters, j = $1 \ldots F_C$
(Design Polygeny)

Functional Requirements, i = $1 \ldots N$
(Design Pleiotropy)

$$\begin{array}{c|ccc} & DP_1 & \cdots & DP_f \\ \hline FR_1 & a_{11} & \cdots & a_{1f} \\ \vdots & \vdots & \ddots & \vdots \\ FR_N & a_{N1} & \cdots & a_{Nf} \end{array}$$

$$design\ matrix\ \ [A] = [a_{ij}]$$

Design Polygeny
(Design Parameter Interaction with Functional Requirements)

Design Pleiotropy
(Functional Requirement Interaction with Design Parameters)

$$\begin{array}{c|c|cc} a_{11} & a_{12} & \cdots & a_{1f} \\ \hline a_{21} & a_{22} & \cdots & a_{2f} \\ \vdots & \vdots & \cdots & \vdots \\ a_{N1} & a_{N2} & \cdots & a_{Nf} \end{array}$$

Example of Relating Design Pleiotropy back to the Design Equations for FRs

$$FR_1 = a_{11}\,DP_1 + a_{12}DP_2 + \cdots + a_{1f}DP_f$$

$$FR_2 = a_{21}\,DP_1 + a_{22}DP_2 + \cdots + a_{2f}DP_f$$

$$\vdots$$

$$FR_N = a_{N1}\,DP_1 + a_{N2}DP_2 + \cdots + a_{Nf}DP_f$$

[22] We depart from the notation of Altenberg (1997) discussed in Chapter 2, Section 2.3.2 for biological polygeny and pleiotropy in order to remain consistent with the axiomatic notation of the design matrix $[A]$; we depart from this notation slightly through the inversion of the rows and columns of $[A]$, while maintaining the key relationships and structure of its biological analogue $[M]$. Pleiotropy comes from the Greek πλείων pleion, meaning "more", and τρέπειν trepein, meaning "to turn, to convert". It designates the occurrence of a single functional requirement affecting multiple design parameters, and is a hugely important concept rooted in evolutionary biology.

In this construct, the design matrix $[A]$ again comprises the design elements $[a_{ij}]$ that represent the interaction of functional requirements $\{FR_i\}$ in the design with the fitness components of the design approach, the design parameters $\{DP_j\}$. The columns $1 \ldots F_C$ of the design matrix $[A]$, with length $i = 1 \ldots N$, highlight the functional requirements responsible for and guiding the decisions for each design parameter j. This column represents the design polygeny; in a biological context, polygeny represents the number of genes affecting a particular fitness component. More concretely, polygeny describes the occurrence where multiple genes contribute to a particular trait or characteristic of a biological entity. Polygeny can span a spectrum of cases ranging from many genes resulting in a relatively small effect to a few genes driving large effects. In the C^2D context, design polygeny similarly represents the number of functional requirements affecting decisions regarding the setting or establishing of a particular design parameter. As in the biological systems case, design polygeny represents the possibility of coupling through the occurrence where satisficing multiple requirements may require continuous redesigning of a characteristic or attribute of design, given by the design parameter. For example in the table above, design polygeny for DP_1 equates to the number of functional requirements responsible for specifying DP_1 through the design elements $a_{11} \ldots a_{N1}$. Similar to previous usage throughout the work, we use the presence of elements $[a_{ij}]$ to denote the existence of a relationship (i.e. $a_{ij} \in (0,1)$ for our theoretical purposes; however, given insight into specific relationships these design elements more generally represents the strength of the sensitivity between components as discussed in Chapter 2, Section 2.1.2).

Similarly, the rows of the design matrix $[A]$, with length $j = 1 \ldots F_C$, provide the design parameters required to satisfy each functional requirement i. This row vector represents the design pleiotropy, which in the biological context represents the fitness components controlled from a particular gene. In particular, pleiotropy corresponds to the case where an individual design controls multiple characteristics or traits of a biological entity. In the context of C^2D, design pleiotropy likewise represents all of the designer parameters necessitated by a single functional requirement. As in the biological case, design pleiotropy corresponds to the case where an individual functional requirement controls multiple characteristics or traits in a design, as given by the design parameters. The occurrence of design pleiotropy represents a non-ideal case of design where the number of design parameters exceed the number of functional requirements, with either redundancy or design coupling. In an ideal case, each functional requirement should only necessitate a designer to make modifications to one aspect of a design, *i.e.* ensuring that the design parameters remain uncoupled. However, in a coupled case functional requirements require changes to multiple design parameters and introduces complexity to a design.

The elements in the design matrix represents the relationships between the functional requirements and the design parameters necessary to meet those requirements. Any functional requirement that shares a design parameter, *i.e.* any design parameter with a design polygeny greater than one, quickly reveals interdependencies in a design. This general approach of using the design matrix $[A]$, builds on the concepts of the design structure matrix from Steward (1981). As seen above the design matrix itself, central to the concepts of design structure matrices, provides a way to determine quickly what design elements receive inputs from one another through its off-diagonal elements or, in other words, through the number of edges in the design. This theory, commonly adapted within systems engineering, has its theoretical backing in mathematics, particularly graph theory, and computer science. For example, consider the example given in sample equation (3.1) for a design that contains nine functional requirements and nine design parameters. In the particular example shown, the design elements form a lower triangular matrix. Although there are multiple obvious dependencies, this construction case corresponds to a *decoupled* design as the piecewise solution of the design matrix remains feasible, *i.e.* the problem remains one of reducible complexity. We adopt definitions of coupling from discussions by Suh (1990) and by El-Haik and Roy (2005). We provide additional examples, to include of *uncoupled* and *coupled* design problems, in Section 3.3.5 subsequently and in Appendix I-K.

$$[A] = [a_{ij}] = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 & 1 & 0 & 1 & 1 \end{bmatrix} \tag{3.1}$$

Where:

$a_{ij} \in (0,1)$, 0 and 1 equates to the respective absence or presence of an interaction
$i = 1 \ldots N$, functional requirements $\{FR_i\}$; $j = 1 \ldots f$, design parameters $\{DP_j\}$

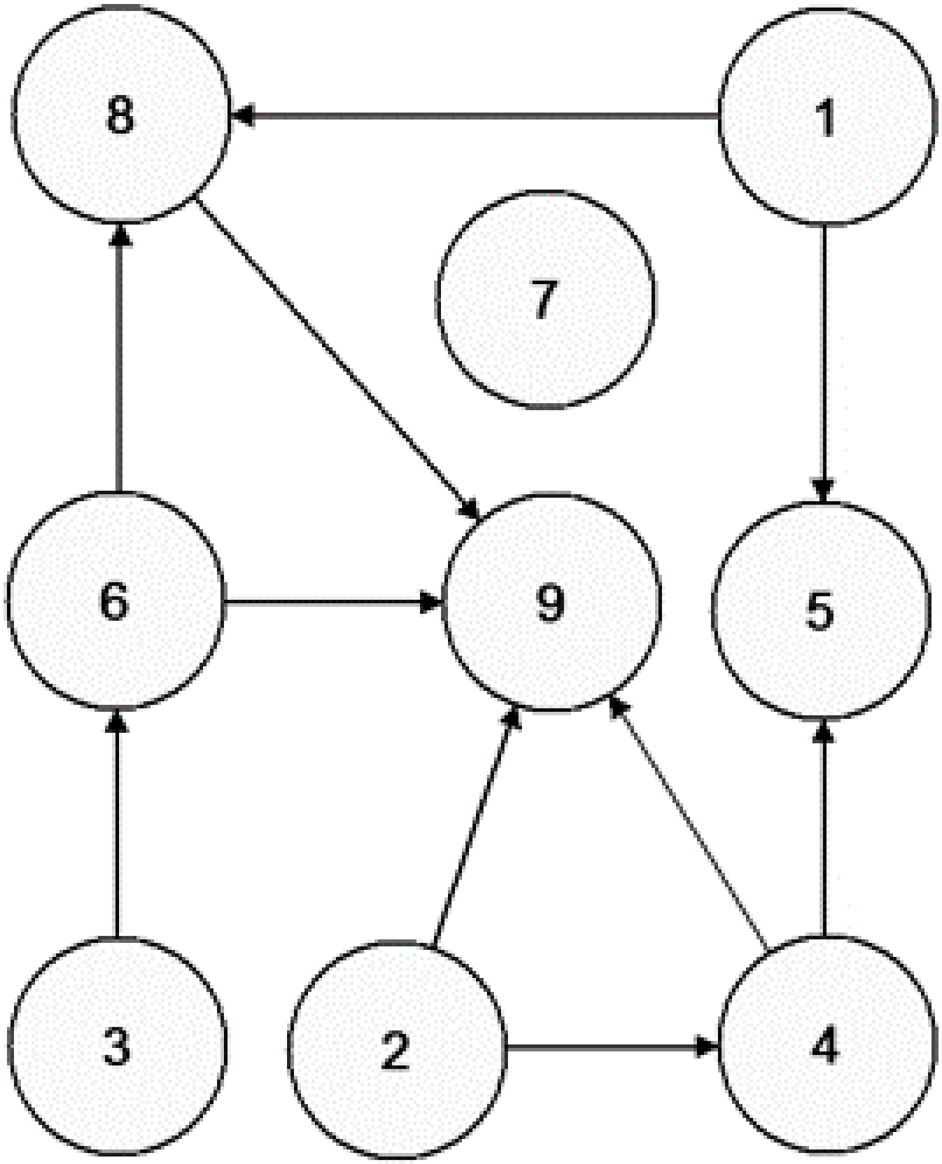


Figure 3.2 Directed Graph Representation of Relationships between Requirements. In this directed graph each edge represents an interdependency in the design between a pair of functional requirements vis-à-vis a design parameter. In the case of the vertex corresponding to functional requirement seven, the functional requirement remains independent as it only depends on its corresponding design parameter; therefore, it remains disconnected. Both the matrix in equation (3.1) and the directed graph above clearly show the high degree of interdependency that exists in functional requirement nine with its preceding design selections. This phenomenon mirrors the path-dependent occurrence of lock-in; for example, functional requirement nine occurred last in the design process and its solution remains limited in range based on each of its preceding dependencies. Later design decisions exhibit increased levels of path dependency due to a premature convergence on a suboptimal design decision (Kogut and Zander 1992; Rycroft and Kash 2010).

This design matrix and graph similarly represents the inputs to the production possibility space of design as discussed earlier in equation (2.34), reproduced below in equation (3.2). These inputs, as defined, give rise to the fitness of the design. This fitness represents, as previously discussed, the degree that the design range, specified by the design matrix $[A]$, meets the performance requirements of a system.

$$P_{\substack{Design \\ Space}} = \{f(\{FRs\},\{DPs\},f_d):\{FRs\},\{DPs\} \in \Re_{+}^{N},\ f_d \in \Re_{+}^{M}:\{FRs\} \wedge \{DPs\} \rightarrow f_d\} \quad (3.2)$$

We focus on the emergence of fitness resulting from the complex relationships between design elements, *i.e.* the role interdependencies have between design parameters and the resulting fitness of design efforts over time. By definition, this approach requires focusing on both the *coupled* and *decoupled* design cases where the design matrix includes off-diagonal elements and on the *uncoupled* design case with zero interdependencies in the design where the design matrix equals a design identity $[I_N]_{ij}$ matrix (cf. Section 3.3.5).[23] In order to accomplish this examination, we next explain the NK approach to creating theoretical fitness values for multiple landscapes; these fitness values depend on the number of functional requirements in the design and the level of interdependencies between design elements in the design. We then introduce aspects of searching this space in Section 3.3, through the introduction of the designer and the design-team. These designers provide for the set of agent-based decision-making units used to search the design space.

3.2.2 Generating NK and C²D Fitness Values

As discussed earlier in Chapter 1, design seldom enjoys the benefit of an uncoupled design with clean closed form utility functions. Design-teams must often navigate a complex terrain of varying

[23] The definitions of the various aspects of design coupling follows from discussions by Suh (1990) and by El-Haik and Roy (2005). The *decoupled design* case represents either an upper triangular design matrix or lower triangular design matrix by definition, whereas the *coupled design matrix* represents a full matrix. The *decoupled design* results in a design space that remains solvable through the sequential solution of design parameters, *i.e.* solving design parameters in a specific sequence conveyed by the design matrix (e.g. solving for $j = 2$ then $j = 1$) ensures the independence of each functional requirement. The *coupled design* represents a full matrix with off-diagonal elements on both the upper and lower triangular sections of the design matrix. In the case of the *coupled design,* the design remains highly rugged. These *coupled designs* represent cases that often comprise the optimality of a design solution; typically, these compromises in design arise from the loss of freedom or path independence in problem solving (El-Haik and Roy 2005). The design diagonal matrix also, in this case, forms a design identity matrix $[I_N]_{ij}$ that equates to δ_{ij} when using Kronecker delta notation where $\delta_{ij} = 0$ if $i \neq j$ and $\delta_{ij} = 1$ if $i = j$. When the design matrix comprises functional requirements i that *only* depend on corresponding design parameters j the design matrix $[A]$ remains a diagonal and uncoupled matrix, *i.e.* leaving the design matrix an identity matrix with a trace of N number of functional requirements.

levels of fitness and multiple competing solutions driven by interdependent and often non-linear relationships between design elements. This complex space defined by the *design landscape* represents an intellectual search domain where its fitness characteristics equate to the ability of a design concept to fulfill requirements. The metaphor of natural selection applied in the C^{2}D approach represents the ability of the designer to quickly adapt, ideate, and find solutions on the *design landscape*. In this metaphor, fitness values provides a measure of the ability for any real positive semi-definite combination of design elements making up a design range to meet the performance requirements of the system, *i.e.* the required system range. We relate the design fitness (f_D^*) to the relative relationship of the design information (I), common range (CR), system range (SR), and design range (DR) discussed from Chapter 2, Section 2.1.2. The theoretical connection provided by equation (3.3) allows for the linkage of the fitness values derived from the concepts of axiomatic design and performance. We demonstrate an example of its usage in Section 3.2.2.2 where we have an understanding of the notional relationships between these variables.

$$\overline{f_D^*} = \frac{1}{N}\sum_{FR_i=1}^{N}\left(\left(1-\frac{I}{|SR|}\right)\frac{|CR|}{|SR|}\right)_i = \frac{1}{N}\sum_{FR_i=1}^{N}\left(\frac{-\left(|CR| * \left(\ln\left(\frac{|SR|}{|CR|}\right) - |SR|\ln 2\right)\right)}{((|SR|)^2 \ln 2)}\right)_i \quad (3.3)$$

In the C^{2}D approach, this concept of fitness underpins the theoretical framework. Fitness enables the decision-making processes of the designers and design-team by providing a benchmark of current performance for the designer, *i.e.* it provides the essential factor in the natural selection dynamic for the framework. However, we generally use the NK construct as a model to randomly generated fitness values; this method utilizes the size N of a design (as measured through the number of functional requirements) and its complexity K (as measured by the number of edges generated by the design matrix). We provide an example of how the NK implementation occurs within the C^{2}D framework in Figures 3.3 – 3.4 and Table 3.2 using the example equation (3.4).

$$[A] = [a_{ij}] = \{FR_i\}\left\{\overbrace{\begin{bmatrix}1 & 1 & 0\\ 0 & 1 & 1\\ 1 & 0 & 1\end{bmatrix}}^{\{DP_j\}}\right. \quad (3.4)$$

Where:

$a_{ij} \in (0,1)$, 0 and 1 equates to the respective absence or presence of an interaction
$i = 1 \ldots N$, functional requirements $\{FR_i\}$; $j = 1 \ldots F_C$, design parameters $\{DP_j\}$

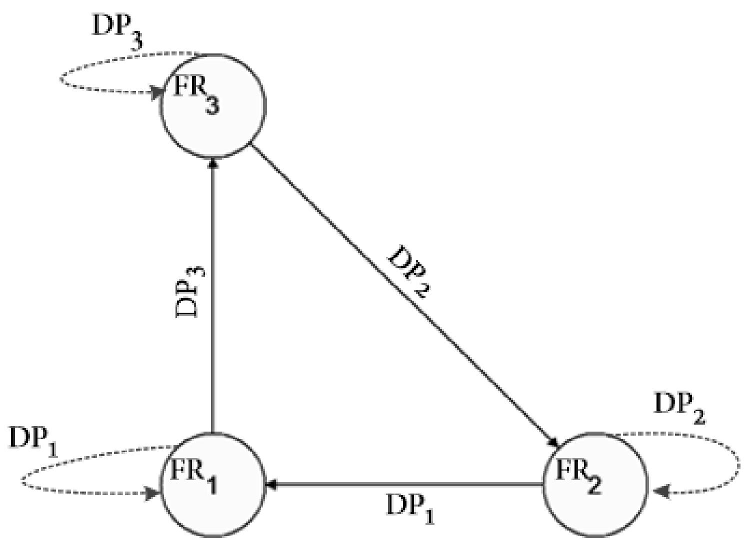


Figure 3.3 Relating Dependencies between Requirements through Design Parameters. Relationships between functional requirements (dashed loops represent the inherent self-dependencies between a functional requirement and its design parameter, future depictions omit this as it is an implied dependency).

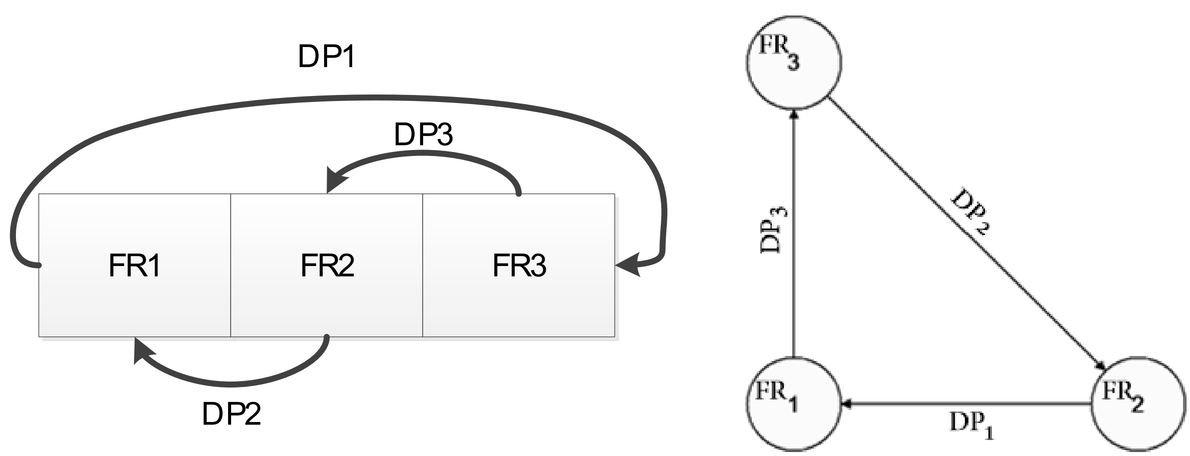


Figure 3.4 Coupled Design Relationship Example ($N = 3, K = 1$). The N represents the number of functional requirements in the design in one of two binary states (interacting or non-interacting). The K represents the degree of interactivity or interdependency present in the design matrix. The directed graph representation (right) provides an equivalent representation of the block representation (left). The blocks and vertices represent a combination of possible binary states among functional requirements, each of these functional requirements receive a randomly generated fitness value based on its level of dependency (cf. Table 3.2) with other functional requirements. In this example, each requirement depends on only one of itself and its right neighbor resulting in the value of $K = 1$.

Table 3.2 Generating Random Fitness Values for $N = 3$ and $K = 1$

FR_1	FR_2	FR_3	$f(DP_1)$	$f(DP_2)$	$f(DP_3)$	$\overline{f_D}$
0	0	0	0.34	0.17	0.73	0.41
0	0	1	0.34	0.73	0.32	0.46
0	1	0	0.17	0.99	0.73	0.63
0	1	1	0.17	0.67	0.32	0.38
1	0	0	0.67	0.17	0.34	0.39
1	0	1	0.67	0.73	0.32	0.57
1	1	0	0.32	0.99	0.34	0.55
1	1	1	0.32	0.67	0.32	0.43

Generating the random fitness values shown in Table 3.2 follows from a routine based on the work by Kauffman (1993) that captures the role that interdependency K has on the overall fitness of a landscape.[24] Conceptually this routine considers how many neighbors share a dependency with the functional requirement in question; when these dependencies occur, the routine establishes fitness values based on the occurrence of the resulting state combinations between, in the context of C^2D, dependent functional requirements. These fitness values describe each state combination using values from a uniform normal distribution between zero and one, with a mean equal to one-half. Each design parameter i depends on its own fitness contribution $f(DP_i)$ as well as the fitness contribution from K other design parameters. In this construction, the possible state for each design element represents either the existence or lack of relationship between a functional requirement and its corresponding design parameter, *i.e.* $a_{ij} \in (0,1)$. In this instance, where the possible

[24] We validate the implementation of this concept in the C^2D design landscape, as discussed in Chapter 4, through its comparison to the data published in Kauffman (1993) and other NK algorithms, such as the Sendero model by Vidgen and Padget (2009), as implemented in the Repast agent-based simulation toolkit. Our C^2D implementation uses general equations from Altenberg (1997), as well as allowing direct table entries, to approximate this approach and ensure consistency with the general findings from Kauffman (1993).

number of states represents a binary choice, the maximum number of possible states at a binary location follows from $S = 2^N$ where N represents the number of functional requirements, in this example the number of states equals $2^3 = 8$.

In the above example shown in Table 3.2, each requirement depends only on its neighboring requirement to the right.[25] As a result, $K = 1$ and the number of edges divided by the number of vertices equals to one. In this example, FR_1 depends on FR_2, FR_2 depends on FR_3, and FR_3 depends on FR_1. This dependence means that, for example in the case of FR_1, random fitness values depends on four possible state combinations with FR_2, *i.e.* (00), (01), (10), and (11). Each of these four possible states corresponds to a randomly drawn fitness value from the uniform normal range between zero and one with a mean at one-half as mentioned earlier. Similarly, in the case of FR_2 and FR_3, the fitness values depend on four possible state combinations with FR_3 and FR_1 respectively. Each of these states similarly receive randomly drawn fitness values. The overall number of required fitness values represents the number of unique possible states for the design matrix required by the given degree of interdependency and size of a design. This relationship to the number of required unique states R_D for the overall design space depends on both the number of functional design requirements N and the degree K of interactions between design elements. Equation (3.5) and equation (3.6) provides these relationships. The required states represent the number of random fitness values required to describe the design space; however, the procedural assignment of these values for a given K give rise to the NK characteristics.

$$R_D = \left(2^{(K+1)}\right)N \tag{3.5}$$

$$R_{FR_i} = 2^{(K+1)} \tag{3.6}$$

In the above example, this means that the design matrix requires $2^{(K+1)}N$ or 12 unique random fitness values, arranged in a manner to reflect its interdependencies, to describe its fitness. The arrangement of the fitness values, as in seen in Table 3.2, follows from the same binary table method described by Kauffman (1993) and from Vidgen and Padget (2009). Averaging these arranged fitness values across each of its eight possible binary states provides for the eight fitness

[25] On the binary string, the right most neighbor for the last requirement, *i.e.* FR_3, depends on the first requirement, *i.e.* FR_1.

values required to describe the fitness landscape. We also modify the example presented to compare a completely uncoupled and a maximally coupled case. We present a comparison of these cases in Table 3.3 and Figure 3.5 below. We also provide additional clarifying examples in Section 3.2.2.3 and in the appendices (cf. Appendix F and Appendix G).[26] We provide a comparison of the mean fitness values for the optima of these landscapes over multiple runs for various combinations of N and K in Figure 3.6. The following discusses what the impact of these differences in the uncoupled and maximally coupled representations:

- Uncoupled Design ($N = 3$ and $K = 0$)
  - According to the above equations (3.5-3.6), the uncoupled design example requires six overall state combinations to describe its fitness. Each of the three functional requirements in this case necessitates two state combinations. In other words, the relationships between each functional requirement and the design parameters remain completely independent and satisfying the functional requirements depends only on how well the functional requirement matches the true systems range and how well its corresponding design parameter matches to a design parameter. Recalling from Chapter 2, in the instance where $K = 0$ the design landscape gives rise to a maximally smooth landscape.
- Maximally Coupled Design ($N = 3$ and $K = N - 1 = 2$)
  - According to the above equations (3.5-3.6), the uncoupled design example requires 24 overall state combinations to describe its fitness. Each of the three functional requirements in this case necessitates eight state combinations, one state for every possible binary location. In this case, each design element depends on every other design element and results in maximal interdependencies between design decisions. Recalling from Chapter 2, in the instance where $K = N - 1$ the design landscape gives rise to a maximally rugged terrain.

[26] So far, we have discussed the elements of the design matrix in terms of N and K and only in terms of a binary choice, the presence or absence of a relationship; however, not all interdependencies in design hold equal weight when considering their contribution to complexity. Part of the ongoing research for the C^2D framework includes the incorporation of the sensitivity of the interdependencies between the requirements and design parameters as a weighing factor in the design matrix $\lambda_{ij} = \partial FR_i / \partial DP_j$ (cf. Section 2.1.2 of Chapter 2). This weighting can provide a realistic mapping from design sensitivity into the NK approach used in the C^2D framework.

Table 3.3 Generating Random Fitness Values Using the NK Approach

$N = 3$ and $K = 0$

FR_1	FR_2	FR_3	$f(DP_1)$	$f(DP_2)$	$f(DP_3)$	$\overline{f_D}$
0	0	0	0.69	0.61	0.06	0.46
0	0	1	0.69	0.61	0.66	0.66
0	1	0	0.69	0.42	0.06	0.39
0	1	1	0.69	0.42	0.66	0.59
1	0	0	0.45	0.61	0.06	0.38
1	0	1	0.45	0.61	0.66	0.58
1	1	0	0.45	0.42	0.06	0.31
1	1	1	0.45	0.42	0.66	0.51

$N = 3$ and $K = N - 1 = 2$

FR_1	FR_2	FR_3	$f(DP_1)$	$f(DP_2)$	$f(DP_3)$	$\overline{f_D}$
0	0	0	0.03	0.52	0.69	0.41
0	0	1	0.75	0.74	0.50	0.66
0	1	0	0.60	0.80	0.71	0.70
0	1	1	0.00	0.66	0.95	0.54
1	0	0	0.46	0.37	0.39	0.41
1	0	1	0.99	0.24	0.88	0.70
1	1	0	0.05	0.39	0.14	0.19
1	1	1	0.04	0.83	0.32	0.40

Uncoupled Design

$$[A] = [a_{ij}] = \{FR_i\}\left\{\overbrace{\begin{bmatrix}1 & 0 & 0\\ 0 & 1 & 0\\ 0 & 0 & 1\end{bmatrix}}^{\{DP_j\}}\right.$$

Coupled Design

$$[A] = [a_{ij}] = \{FR_i\}\left\{\overbrace{\begin{bmatrix}1 & 1 & 1\\ 1 & 1 & 1\\ 1 & 1 & 1\end{bmatrix}}^{\{DP_j\}}\right.$$

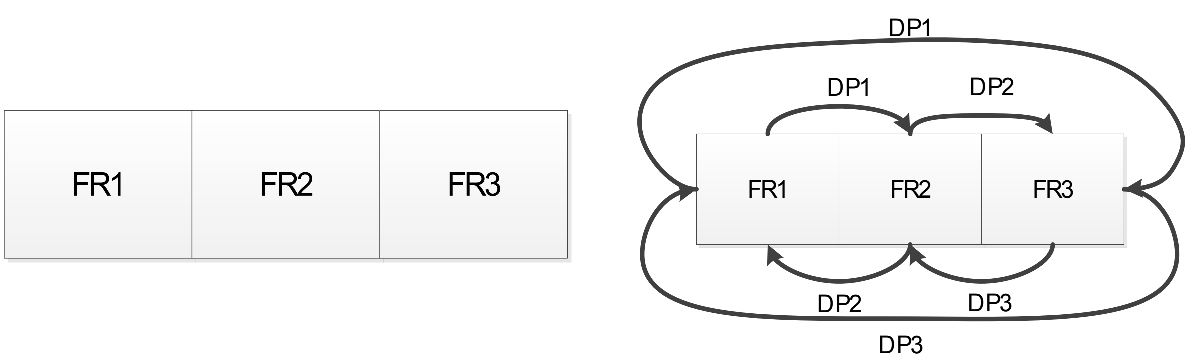


Figure 3.5 Interdependency Tracing for N=3 and K=0 (left) and N=3 and K=2 (right)

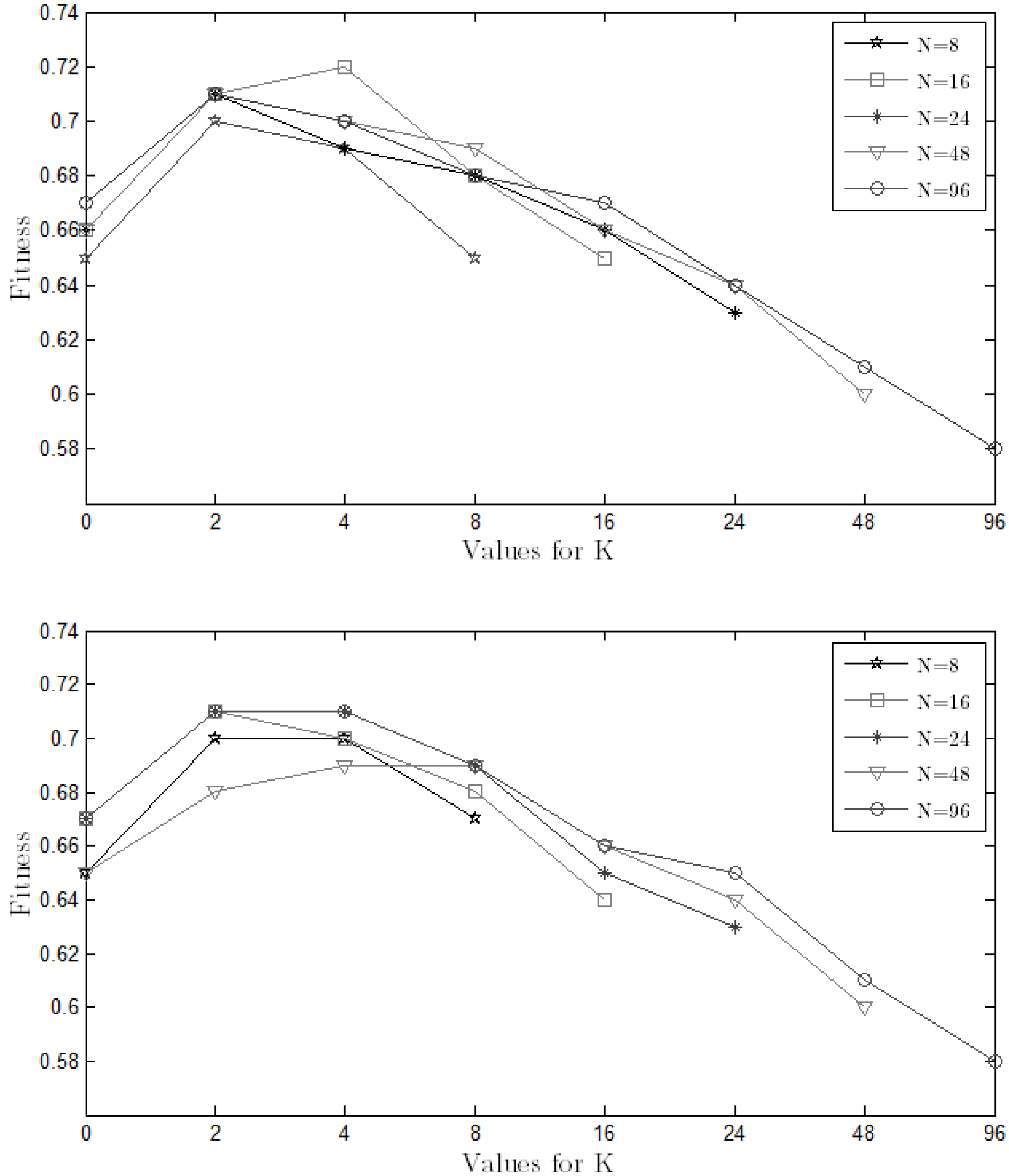
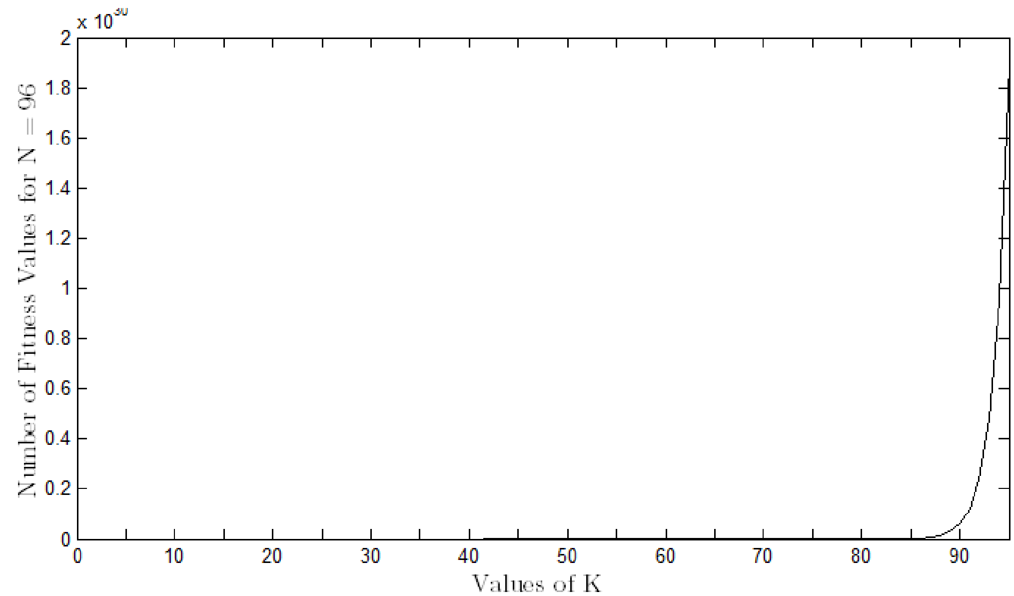


Figure 3.6 Mean Optima Fitness Values with Nearest-Neighbor Interactions for N and K. This figure compares the C²D table approximation approach over 100 runs (top) and the mean fitness values from Kauffman (1993) [bottom]. In order to establish an equivalent NK landscape to the one from Kauffman (1993), the C²D NetLogo model generates fitness values from generalized relationships, and table values (cf. 3.2.2.1). Altenberg (1997) gives the expected number of optima as $E(n) = 2^N/N + 1$ for the $K = N - 1$ case and we use table values and a smoothness factor to approximate other intermediate cases of the K variable. The model rescales the landscape to ensure each optimum has the average values reported from Kauffman (1993) displayed in the bottom figure and the expected variation from Altenberg (1997). This variation for intermediate values of K follows variance from $\sigma^2 = (1/12)(K+1)/N[K + 1 + 2(K+2)\ln(K+1)]$ for values of $N \geq 8$ and from uniform normal values for small values of the K variable.

Although the total number of required states in a design matrix represents an important factor in describing the relative complexity of a design space, the essential procedure for generating the average fitness values for the landscape centers on the structuring of the random values in the binary table shown. The structuring of this binary table relates to the interdependencies within the design; each of these interdependencies corresponds to a possible new state with its own set of fitness contributions. For example the case of $K = 1$ results in binary combinations of (00), (01), (10), or (11). This quantity of binary combinations in the example follows $R_{FR_i} = 2^{K+1} = 4$. The fitness contributions from each of the two design parameters involved (i.e. itself and K others) results in four corresponding fitness contributions for each of these possible four states. In the case where $N = 3$, each of those four fitness values repeats twice, formally $2^N/R_{FR_i}$ times. After the assignment of these $R_D = \left(2^{(K+1)}\right)N$ unique fitness contributions to the fitness tables, averaging occurs across the randomly generated fitness contributions at each possible binary location (*i.e.* the mean fitness contribution for a requirement i equals $\overline{f_{D_i}} = \sum_{j=1}^{f} f(DP_j)/f$). In this sense, the mean fitness contributions of the individual design parameters $j = 1 \ldots f$ for a functional requirement i provides a measure of the design pleiotropy for each binary position.[27] The resulting mean of the fitness contributions from each design parameter at each of the binary locations provides the mean fitness value $(\overline{f_D})$ used in the modelling the NK design fitness landscape. As seen in the above examples, the relative fitness contributions of a design parameter depends on itself and on K other design parameters. In this context, design often represents the process of optimizing the average fitness of design contributions. In the context of Pareto optimality, the presence of K often represents the instance where optimization of fitness results in the condition where a design parameter cannot improve its performance without decreasing the performance of at least K other design parameters. As seen Figure 3.7, the time taken to generate these fitness values quickly grows from trivial level when $K = 0$, $R_D = \left(2^{(K+1)}\right)N = 2N$ to a computational challenge for most agent-based modelling platforms when $K = 95$, $R_D = (39{,}614{,}081{,}257{,}132{,}168{,}796{,}771{,}975{,}168)\ N$ or $(3.9614\ x\ 10^{28})N$. Because of this computational demand, we utilize approximations of this method in the C^{2}D implementation to allow for timelier modelling of the team and search dynamics, the purpose of the C^{2}D framework.

[27] In the biological analogy, the fitness contributes from the design parameters represent allele values for a particular locus. In this instance, the loci correspond to the functional requirements of a design matrix.



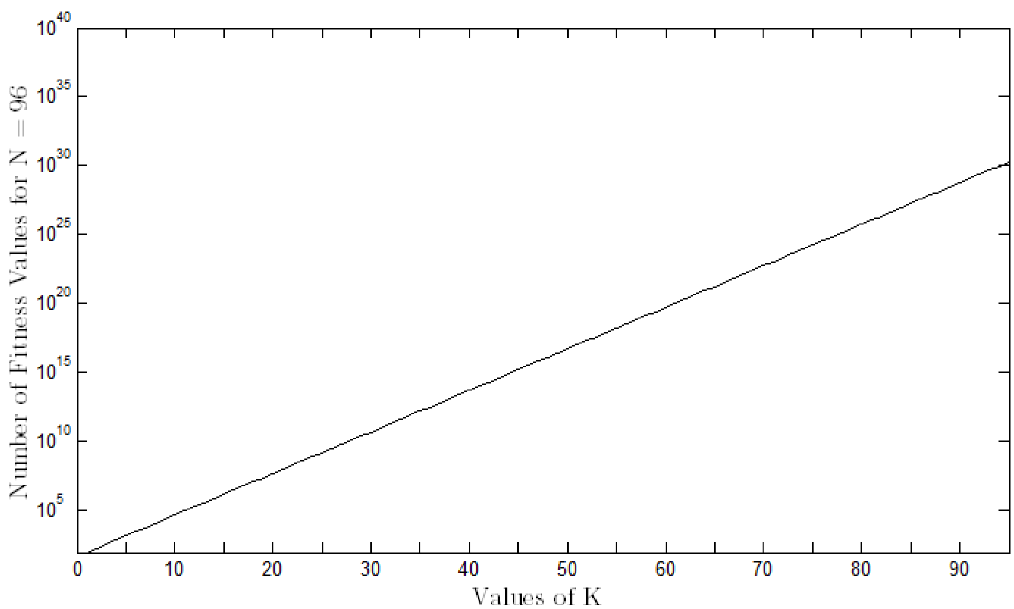


Figure 3.7 Required Number of Fitness Values for K Values. Representation of the required number of randomly generated fitness values corresponding to $R_D = N(2^{(K+1)})$ where $N = 96$, in a linear plot (top) and log-linear plot (bottom)

3.2.2.1 GENERALIZED RELATIONSHIPS FOR THE NK MODEL

In the above case, shown in Table 3.3 where $K = 0$, each of the functional requirement depends only on its corresponding design parameter, therefore each functional requirement has one of two randomly drawn fitness values that correspond to its binary state of zero or one. In contrast, the above case where $K = N - 1$, the functional contribution of the design parameters depends on every other functional requirement and as a result each contribution from the design parameter equates to a distinct fitness value. For large values of K this quickly leads to an unwieldy required amount of random fitness values to establish the design frontier. Instead of computing each of these values, we utilize some theoretical relationships between N and K from the literature. Specifically, we turn to generalizable relationships between these fitness values and the size of K and N from Altenberg (1997), derived from empirical observations derived across multiple runs. For the case of $K = 0$, the landscape becomes the simple additive Gaussian multi-locus model discussed in Chapter 2, Section 2.3.1. For large values of N and K (i.e. approximately $K > 8 < N - 1$), the fitness values of the local optima equate to an asymptotically normal distribution with a mean and variance centered according to the derived equations (3.7-3.8) from Altenberg (1997). In the uniform distribution case, used in C^2D, the expected values for the landscape uses the corresponding values for the mean and standard deviation $\mu = 1/2$ and $\sigma = \sqrt{1/12}$ respectively. The following deduced relationships for intermediate values of K discussed by Altenberg (1997) provides an expected mean for local optima, and an expected variation for local optima.

$$E[\mu] = \mu + \sigma\sqrt{\frac{2\ln(K+1)}{(K+1)}} \tag{3.7}$$

$$E[\sigma^2] = \frac{\sigma^2(K+1)}{N[K+1+2(K+1)\ln(K+1)]} \tag{3.8}$$

For cases with small values of K, *i.e.* approximately $K \leq 8$, the optima share many of their fitness contributions from common design parameters; however, this correlation, as discussed by Altenberg (1993), quickly falls away as the value of K increase. These observed relationships emerge after multiple runs and generations of fitness landscapes under different repeated combinations of the variables N and K. In order to ensure the consistency of the design landscape to the results from Kauffman (1993), Vidgen and Padget (2009), and the summary of findings from Altenberg (1993) for all values of K, we use a three-stage approach in approximating the NK landscape. In order to do this and limit the modelling variability to the experimental team-formation parameters, we restrict the construction of the landscape first to the number of observed optima from Kauffman (1993). We first establish these optima with the expected mean of local optima $E[\mu]$ and the expected variance of local optima $E[\sigma^2]$ from the above equations. The C^2D model then smoothens the landscape before utilizing tables to rescale the landscape, this process of rescaling ensures that local optima maintain consistency to the mean fitness of local optima (nearest neighbor interactions) observed by Kauffman (1993). The model then reapplies the expected variance $E[\sigma^2]$ to the rescaled optima in the landscape in order to allow the local optima to reflect the expected range of fitness values. This approach allows the C^2D experimentation to limit variability due to the construction of the NK landscape while minimizing the time required completing runs at larger values of the variable K. Generation of fitness landscapes using a direct implementation approach for values of K equal to 48 in the C^2D model took on average in excess of three hours to generate using the Java based NetLogo platform using a standard home PC.[28] Approximating the landscape, allows the experimentation to focus testing on the design-team dynamics and search behaviors under various approximate NK configurations quickly. Figure 3.6 demonstrates a strong correspondence between the approximated landscape and the values from Kauffman (1993).

3.2.2.2 Note on Calculating Fitness from Known Design and System Ranges

We generally use the NK model when we have a limited understanding of the design space, and for purposes of this research, we are looking for generalizable insights regarding complexity that allow us to remain maximally indifferent to the exact specifications between parameters and requirements. However, the framework presented in C^2D remains extensible to the case where we can discern the relationships between functional requirements and design parameters. Let us consider the example of designing a cell phone based on three simple functional user requirements:

- A phone with talk time between 8-10 hours;

[28] All results in the research used a home PC with an Intel® Core ™ i7-3770T CPU @ 2.50 GHz 2.50GHz x64-based processor with 8.00 GB of installed RAM running Windows® 8.1 64-bit Operating System.

- A phone with standby time between 250 and 325 hours; and,
- A phone with a touch screen surface between 5000 mm^2 and 6000 mm^2

Let us assume that we are now evaluating three different design configurations (i.e. different possible combinations of physical design attributes given by the design parameters) given in Table 3.4. Each of these design options entail different levels of fitness with regard to these requirements above. We present a brief discussion on how we can use principles from Axiomatic Design (AD) from Suh (1990) and the C^{2}D framework to provide fitness values for each of these specific design configurations.

Table 3.4 Design Approach and Dependencies Given by the Revised Design Matrix

	Design Option 1	*Design Option 2*	*Design Option 3*
FR_1 *: Talk time, 8-10 hrs*	5-9 hrs	6-10 hrs	7-12 hrs
FR_2 *: Standby time, 250 and 300 hrs*	240- 285 hrs	250 - 290 hrs	230 - 300 hrs
FR_3 *– Touchscreen, 5000 and 6000* mm^2	4500 – 5500 mm^2	5250 – 6000 mm^2	5000 – 5900 mm^2

We do so by first relating this example to the principles of AD. First, we establish the desired functional requirements as providing a system range (SR) and, similarly, the design options as providing the design range (DR), *i.e.* the ability of a design parameter to respond to functional requirement. When both the SR and the DR align we have a common range (CR) for the design option that translates into workable solutions. The exact relationships between these functional requirements and design parameters give rise to specific likelihood functions or probabilities for the success of the design. In the C^{2}D framework, we consider this likelihood of success in terms of design fitness. We view these likelihoods as arising from the influence of design complexity on this fitness. Specifically we view design complexity as relating weighted interactions between design parameters and functional requirements.

The AD framework from Suh (1990) similarly considers design complexity in terms of a determent to achieving a desired performance state of a system. Suh (1990) explores these probabilities through a broad measure of the information content of design or, moreover, a measure of the probability of obtaining the desired result, given by the functional requirements. We can apply these same principles from the AD framework to translate the concept of information into an analog of design fitness through equation (3.3) in a concrete way.

In the C^{2}D framework, we similarly consider the manner each of the interaction of each design parameter and functional requirement; we view these interactions as providing the fitness characteristics given by the design landscape. In the analogy to AD, a highly fit design requires less information (I) required of a design and has a higher probability of success $P_{\{N\}}$ in meeting all N of the functional requirements. For example in the instance of a coupled design, $K > 0$, the underlying interactions between multiple design parameters and functional requirements gives rise to a conditional probability that all N functional requirements are satisficed. The AD framework represents this conditional probability as $P_{\{N\}} = \prod_{i=1}^{N} P_{i|\{j\}}$ for $\{j\} = \{1, \dots., i-1\}$ given that all other correlated functional requirements $\{FR_j\}_{j=1,\dots,i-1}$ are similarly satisficed. This probability of design success is directly related to the concept of design fitness and, consistent with Suh (1990), it is inversely related to the concept of information. More specifically, the AD framework consider the information content of a coupled design as following from a conditional probability following from $I_d = -\sum_{i=1}^{N} \log_2 P_{i|\{j\}}$ for $\{j\} = \{1, \dots., i-1\}$. As in the AD framework, we can relate this information content and probabilities to design fitness. More specifically, we similarly look to the area of the common range (A_{CR}) of design, the area under the probability distribution function within the common range, as the probability of achieving a specified goal.

We begin by applying our understanding of how each individual design in Table 3.4 above responds to the each of the functional requirements. We can imagine a system where generic fitness scores between zero and one would correspond to the ability of a design range for a particular design option to respond to the system range (i.e. the range required by the functional requirements) fully. Notionally, we can more formally state this relationship as $f_d \propto A_{CR}$, *i.e.* the fitness of a design remains proportionally to the probabilistic ability of a design range to satisfice functional requirements. This satisfaction of requirements probabilistically corresponds to the area of the common range (A_{CR}), where the probabilistic design range and probabilistic system range overlap.

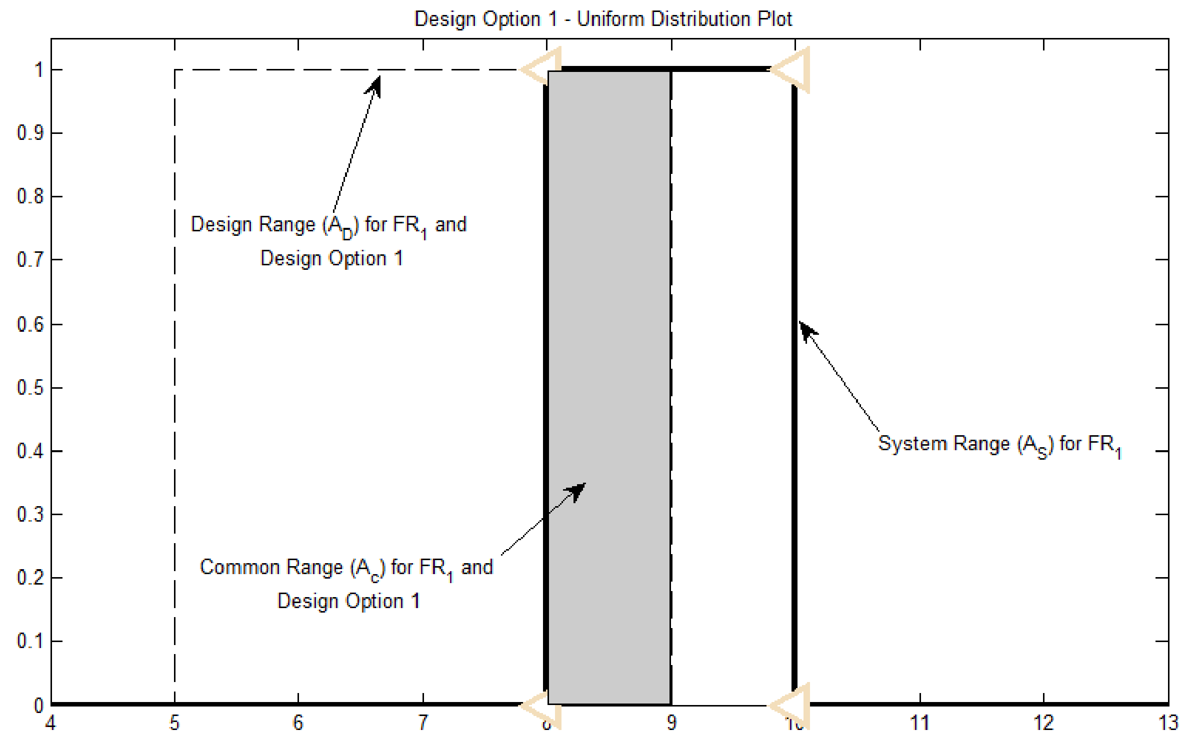
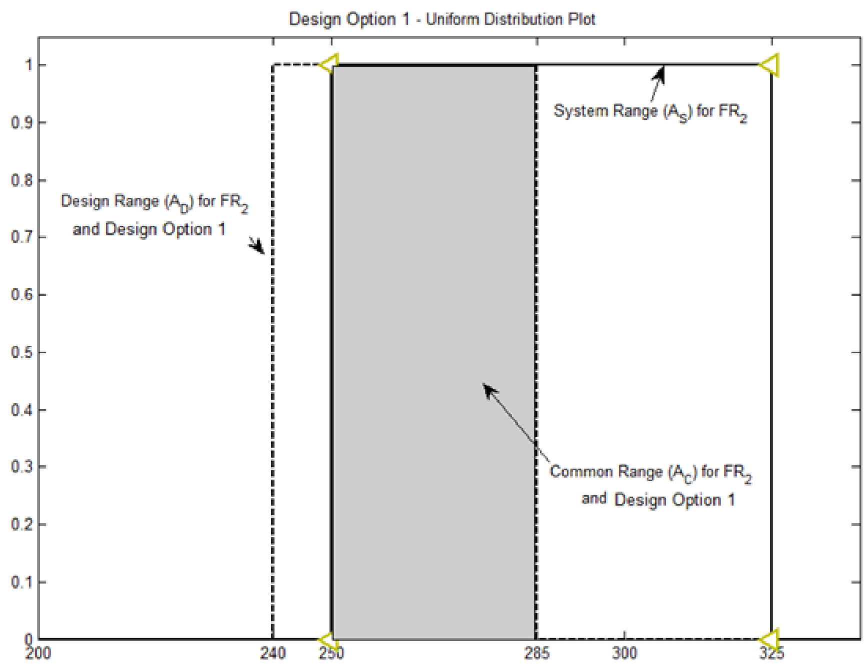


Figure 3.8 Common Range, Design Range, and System Range for Functional Requirement One

In the above figure, we consider the functional requirement of having between eight and ten hours of battery life for a phone and compare it to the fitness of Design Option 1. This requirement of between eight and ten hours establishes the system range for the design. For Design Option 1 (i.e. a particular phone design), the design artefact offers (with a uniform probability distribution) between five and nine hours of battery life. The ability of this particular phone to meet the functional requirements similarly establishes the design range for the artefact of (i.e. $|DR| = 10 - 5 = 5$). As we can see the $A_{DR} \cap A_{SR}$ results in an A_{CR} of approximately 50% of the A_{SR} or another words we have, probabilistically, a one out of two chance (i.e. $|CR|/|SR|$) of achieving the functional requirement of having between eight and ten hours of battery life. From an information perspective, this translates into one bit of information following from the AD equation given by $I = -\log_2 A_{CR} = -\log_2 \frac{|CR|}{|SR|} = -\log_2(0.5)$. This means that this particular design parameter to functional requirement requires some information, *i.e.* one bit, about how the other functional requirements are utilized to be successful. We can build on this by relating it to a relative fitness score as proposed in equation (3.3). We calculate the fitness contribution from this design parameter to this particular functional requirement as 0.25 using the following relationship $f_{FR} =$

$\left(1-\frac{I}{|SR|}\right)\frac{|CR|}{|SR|}$, which reduces to the following $-\left(|CR|(I-\ |SR|)\right)/|SR|^2$ resulting in $-(1*(1-2))/2^4$ and the 0.25 fitness value. We do this for each of the remaining functional requirements in Figure 3.9.



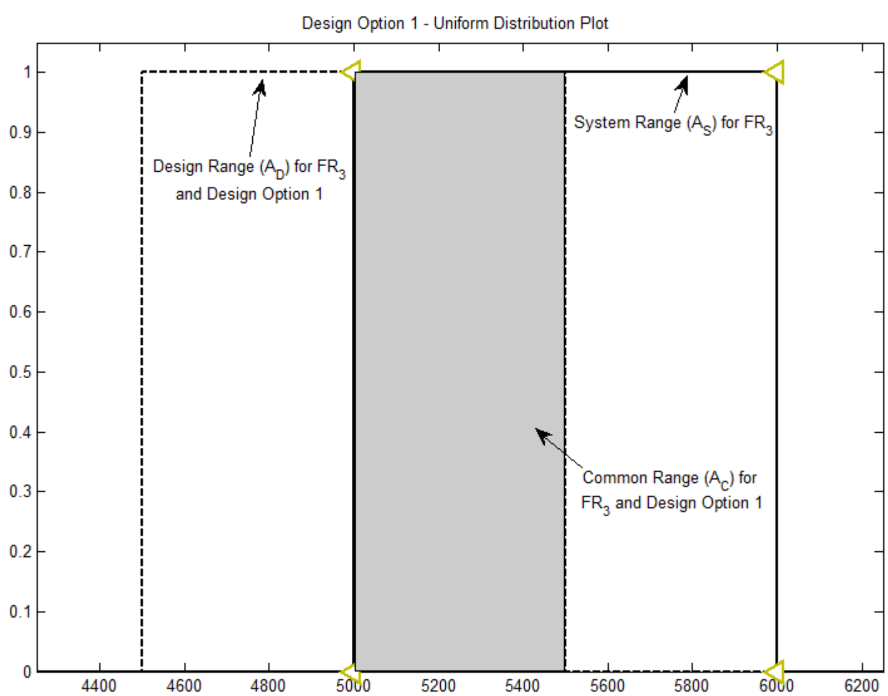
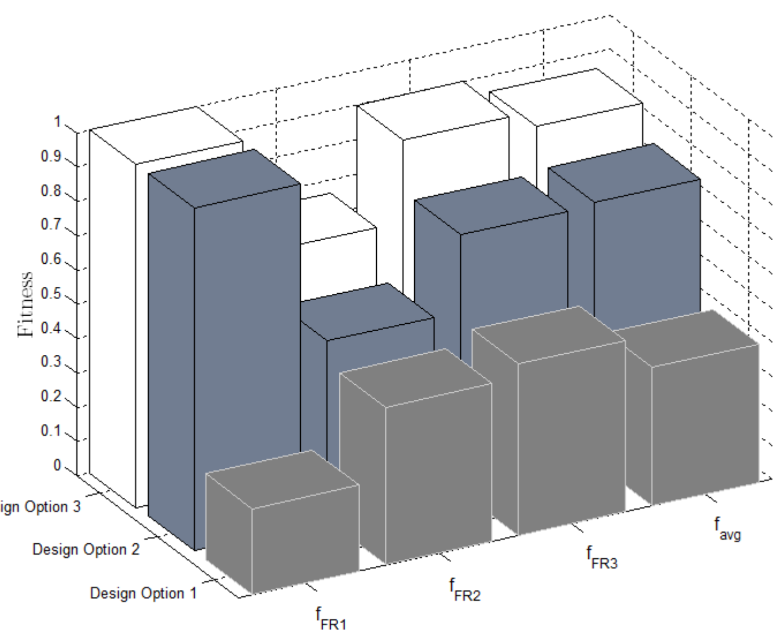


Figure 3.9 Common Range, Design Range, and System Range Example for Functional Requirement Two (top) and Functional Requirement Three (below)

In the above figures, we represented the probability of achieving these requirements using a uniform probability distribution function; however, as part of the greater discussion regarding complexity in C^{2}D, each of these distributions can greatly vary depending on the interconnectedness of design elements. In this example case, we assume that these distributions correctly depict the likelihood of system success.

Table 3.5 Overall Design Approach and Dependencies Given by the Revised Design Matrix

	Design Option 1		*Design Option 2*		*Design Option 3*	
	$Information$ $(bits)$	$Fitness, f_D^*$	$Information$ $(bits)$	$Fitness, f_D^*$	$Information$ $(bits)$	$Fitness, f_D^*$
FR_1 : *Talk time, 8-10 hrs*	1	0.25	0	1	0	1
FR_2 : *Standby time, 250 and 300 hrs*	1.10	0.46	0.91	0.53	0.58	0.66
FR_3 – *Touchscreen, 5000 and 6000 mm*^{2}	1	0.50	0.42	0.75	0.15	0.90



Fitness Averages, from equation (3.3):	$\overline{f_D^*}_1 = 0.40$	$\overline{f_D^*}_2 = 0.76$	$\overline{f_D^*}_3 = 0.85$

These design options in the table with their own unique use of design attributes have various configurations of design parameters to functional requirements. These differences result in varying characteristics of performance and fitness. We view these differences as corresponding to particular locations on a theoretical design landscape; in this instance, the precise values of functional requirements and design parameters are known for each of these particular design options presented. These values provide some insight into a few possible design approaches, here limited to just three design options. In the C^2D approach, we create a theoretical landscape to encompass all possible design approaches. With additional knowledge of the interactions between the design parameters and functional requirements for these options, we can create a value or objective function to represent the overarching design landscape for a particular set of functional requirements. However, when these relationships are unknown we turn to the concepts of a theoretical NK design landscape.

3.2.2.3 Note on the Calculation of Random Fitness Values in the NK Model

In the previous example, we understood fully the system range and ranges of design response for a set of three theoretical cell phones, including their probability distribution characteristics. In the example, the system range and set of design ranges relied on a uniform probability distribution. However, in reality the complexity of the design (the interaction of functional requirements) can result in probabilities distribution functions difficult to discern. Absent any knowledge of these particular resulting distributions, we can look toward the creation of a more generalized landscape based only on the degree of interaction between design parameters and functional requirements through the use of the NK procedure. Although wee envision expanding this approach in future research through the application of weighting factors given knowledge about these underlying relationships, this approach does not require this information. For this example, we can reevaluate a similar example problem where instead of having known design solutions we have a range of factors contributing to the fitness of functional requirements. Here we relate, for illustrative purposes, the same three functional requirements to three design parameters. Here we notice that the satisficing of each requirement depends on neighboring requirements. These interactions between neighboring functional requirements gives rise to a moderately rugged landscape of design between the minimally rugged (i.e. smooth) landscape of $K = 0$ and the maximum rugged case of $K = N - 1 = 2$. We use the procedure for generating these NK fitness values from Kauffman (1993) and from Vidgen and Julian (2009) in Table 3.7.

Table 3.6 Sample Relation between Design Approach and Fitness Values

$N = 3, \quad K = 1$		Design Parameters: Battery Chemistry	Design Parameters: Quiescent Circuitry	Design Parameters: Discharge Circuitry
Functional Requirements	Standby time, 250 and 300 hours	X	X	
	Touchscreen, 5000 and 6000 mm^2		X	X
	Talk time, 8-10 hours	X		X

Table 3.7 Generating Random Fitness Values for $N = 3$ and $K = 1$

Binary Locations			*Fitness for Possible Interactions*			
FR1	FR2	FR3	DP1	DP2	DP3	$\overline{f_D}$
0	0	0	0.35	0.77	0.02	0.38
0	0	1	0.35	0.60	0.75	0.57
0	1	0	0.13	0.94	0.02	0.36
0	1	1	0.13	0.47	0.75	0.45
1	0	0	0.01	0.77	0.88	0.55
1	0	1	0.01	0.60	0.95	0.52
1	1	0	0.09	0.94	0.88	0.63
1	1	1	0.09	0.47	0.95	0.50
					$f_{global\ maximum}$	0.63

We can see in the table above that we have established fitness values for the sample example. In order to generate the fitness values for this landscape we first inspected the functional requirements and their linkages and interdependencies. In Figure 3.10, we highlight these interdependencies. In this figure, each requirement is influenced by its own design parameter (which we omit in the figure for simplicity) as well as the design parameters governing its neighboring functional requirement. In this example, each requirement depends on its neighbor to the right (in the case of the rightmost requirement this dependency loops around to the leftmost requirement).

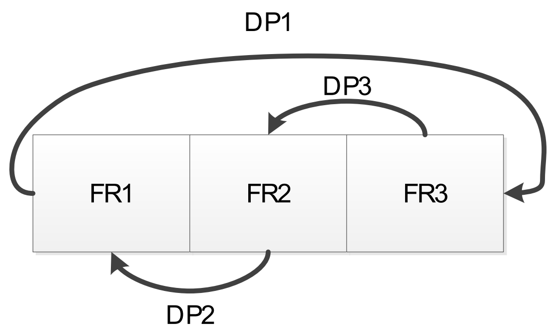


Figure 3.10 Mapping of the Interdependencies between Requirements

What these dependencies translates into is that the for the first binary location, given by FR_1, its fitness depends also on the state of its neighbor FR_2. In other words, we have four fitness values for FR_1 that correspond to one of the four possible states between these requirements (i.e. 00*x*, 01*x*, 10*x*, and 11*x*). We use the '*x*' in these binary locations to represent that a third binary location exists but that this binary locations does not inhibit or constrain the fitness of the remaining binary locations. Similarly, we have four possible states each with their own random fitness values that result from the possible interactions between FR_2 and FR_3 (i.e. *x*00, *x*01, *x*10, and *x*11) and between FR_3 and FR_1 (i.e. 0*x*0, 0*x*1, 1*x*0, and 1*x*1). By then placing these randomly generated values in their binary locations we arrive at the fitness values used by Kauffman (1993). For example, at the first location of possible interactions between the design (i.e. 000) we generate random values in the following way: 1) generate random value for 00*x*, 2) generate random value for *x*00, and 3) generate random value for 0*x*0. We show this result in Table 3.8.

Table 3.8 Generating the First Line of Fitness Values

	$f(DP_1)$	$f(DP_2)$	$f(DP_3)$
000	0.35	0.77	0.02

We then proceed to the next location on the binary string (i.e. 001). Here we similarly generate random values for any unassigned binary locations. More specifically for binary location we: 1) replicate the randomly drawn value for $00x$, 2) generate a new random value for $x01$, and 3) generate a new random value for $0x1$. We show this result in Table 3.9.

Table 3.9 Generating the Second Line of Fitness Values

	$f(DP_1)$	$f(DP_2)$	$f(DP_3)$
000	0.35	0.77	0.02
001	0.35	0.60	0.75

We repeat this procedure for the remaining binary locations in Table 3.10. Arrows represent a repeat of interactions between binary locations. In these repeated locations, we use the same fitness values as drawn previously. In effect when there is no interactions, each functional requirement then only depends on itself being in zero or one, resulting in only two random draws for fitness. Similarly, in the extreme case of $K = N - 1$ each location on the binary string depends on every other binary location.

Table 3.10 Generating the Remaining Fitness Values

	$f(DP_1)$	$f(DP_2)$	$f(DP_3)$	$\overline{f_D}$
000	0.35	0.77	0.02	0.38
001	0.35	0.60	0.75	0.57
010	0.13	0.94	0.02	0.36
011	0.13	0.47	0.75	0.45
100	0.01	0.77	0.88	0.55
101	0.01	0.60	0.95	0.52
110	0.09	0.94	0.88	0.63
111	0.09	0.47	0.95	0.50

Under this established NK procedure from Kauffman (1993) and after Vidgen and Julian (2009), we can then average each of these binary locations to create an average fitness value for each of these particular binary locations. We use these values to help form a fitness landscape; we can see that the resulting design landscape in Figure 3.11 contains multiple optima. To establish this landscape we use a cube, i.e. a polytope of three (γ_3), to correspond to the three functional requirements ($N = 3$). For larger values of N, we reduce dimensionality per the following section.

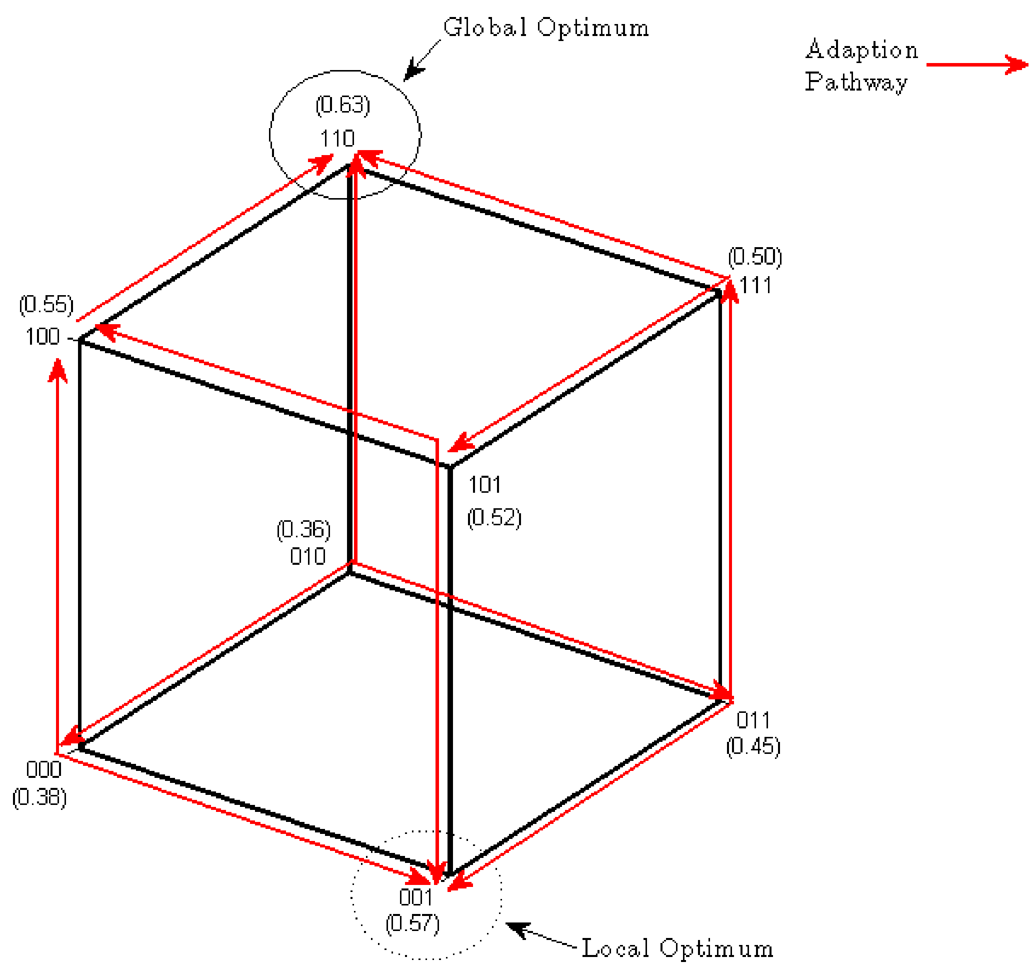
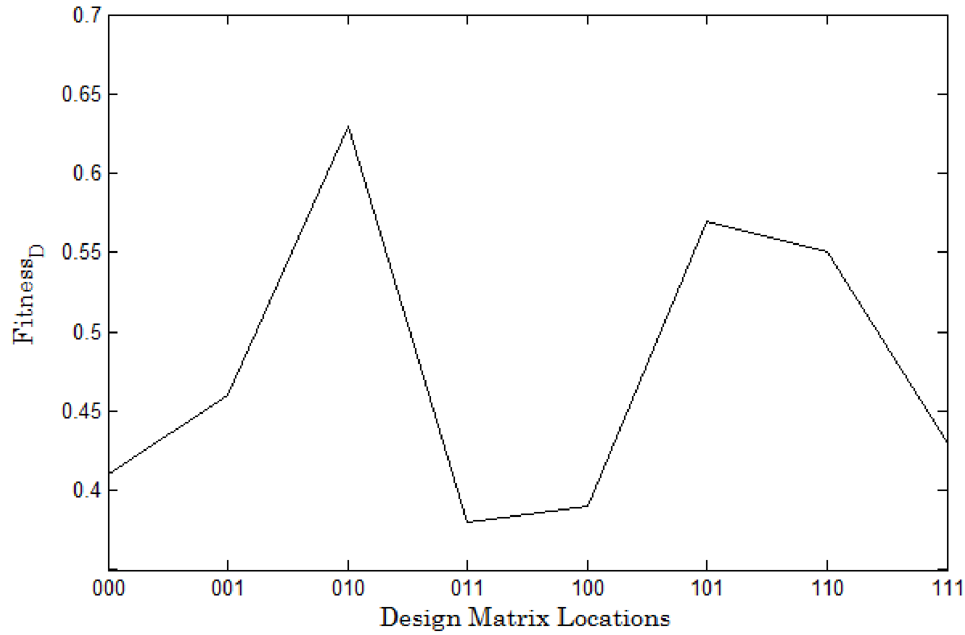


Figure 3.11 Example Design Landscape for Random NK Fitness ($N = 3, K = 1$)

3.2.3 Constructing the NK and C²D Design Landscapes

The design landscape provides a representation of the mapping between the randomly generated fitness values previously discussed. Wright (1932) and later Kauffman (1993) originally envisioned and established this landscape in terms of a hypercube, an n-dimensional analogue of a square ($n = 2$), as discussed by Coxeter (1973). We use the example fitness values from Table 3.2, with results summarized in Figure 3.12 (top), to apply this same approach to the design to arrive at a design landscape in Figure 3.12 (bottom). We then reduce the dimensionality of the hypercube to a representation equivalent to the one used as part of the C^{2}D modelling in Figure 3.13.



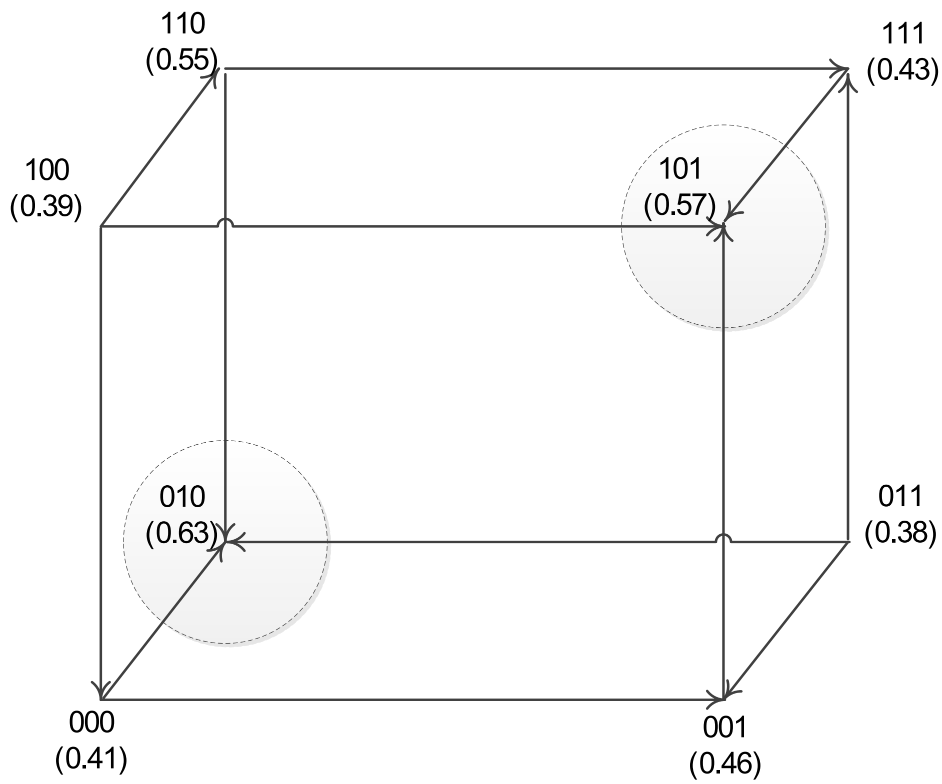


Figure 3.12 Design Fitness as a NK Design Landscape. This figure displays average fitness values $\overline{f_D}$ from the example in Table 3.2 (top) and represents these values as a hypercube (bottom). This hypercube (a polytope-3) corresponds to a system of three functional requirements. Arrows imply possible movements to higher levels of fitness, *i.e.* adaption pathways. As seen in the figure, this $N = 3$ and $K = 1$ example results in two distinct local optima (circled by dashed lines).

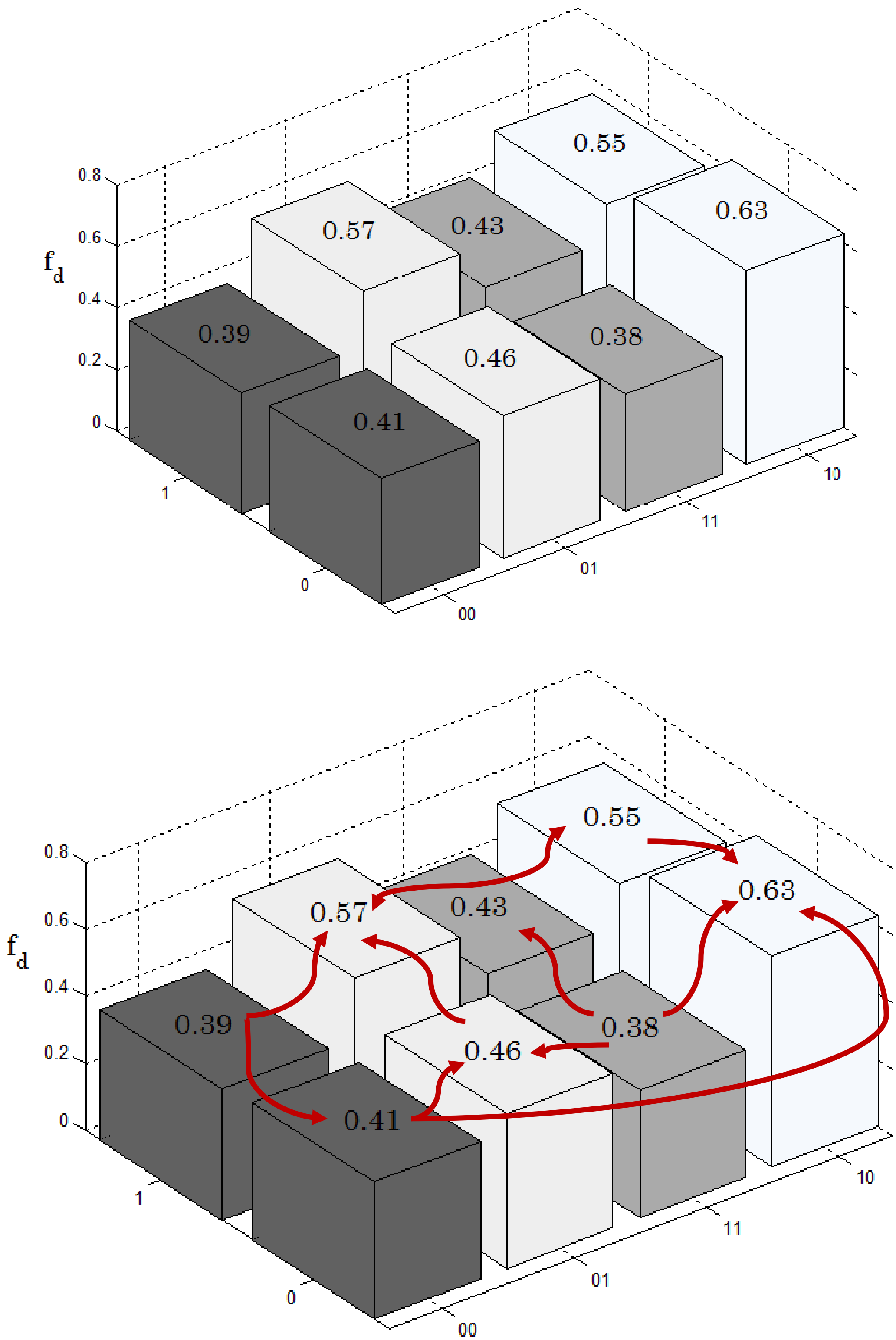


Figure 3.13 *NK* Design Landscape as a 3D-Bar Plot. This plot provides for a visual representation of the *NK* Design Landscape (top) and an overlay of the adaptive or mutagenic pathways available at each location (bottom), generated in MATLAB (cf. Appendix H). We reduce dimensionality for larger polytopes using the same process. This is consistent with methods from Kauffman (1993). The world wraps as a Torus (see connection from patch 000 to 010, same as in the previous hypercube figure).

In order to develop the landscape in a meaningful visualization for the C^{2}D model we similarly rearrange the Boolean cube from Figure 3.12 (bottom) into a landscape of reduced dimensionality. Figure 3.13 above demonstrates this new design landscape. Figure 3.14 below demonstrates the similarity to the design landscape in the C^{2}D model. This C^{2}D landscape differs from that seen in Figure 3.13 in its implementation as the model averages the surrounding eight patches surrounding a fitness point repeatedly in proportion to the relative level of epistasis in the landscape given by K and more specifically the smoothness variable S^* (cf. Section 3.3.4). This parameter smoothens the landscape while still approximating the NK fitness values.

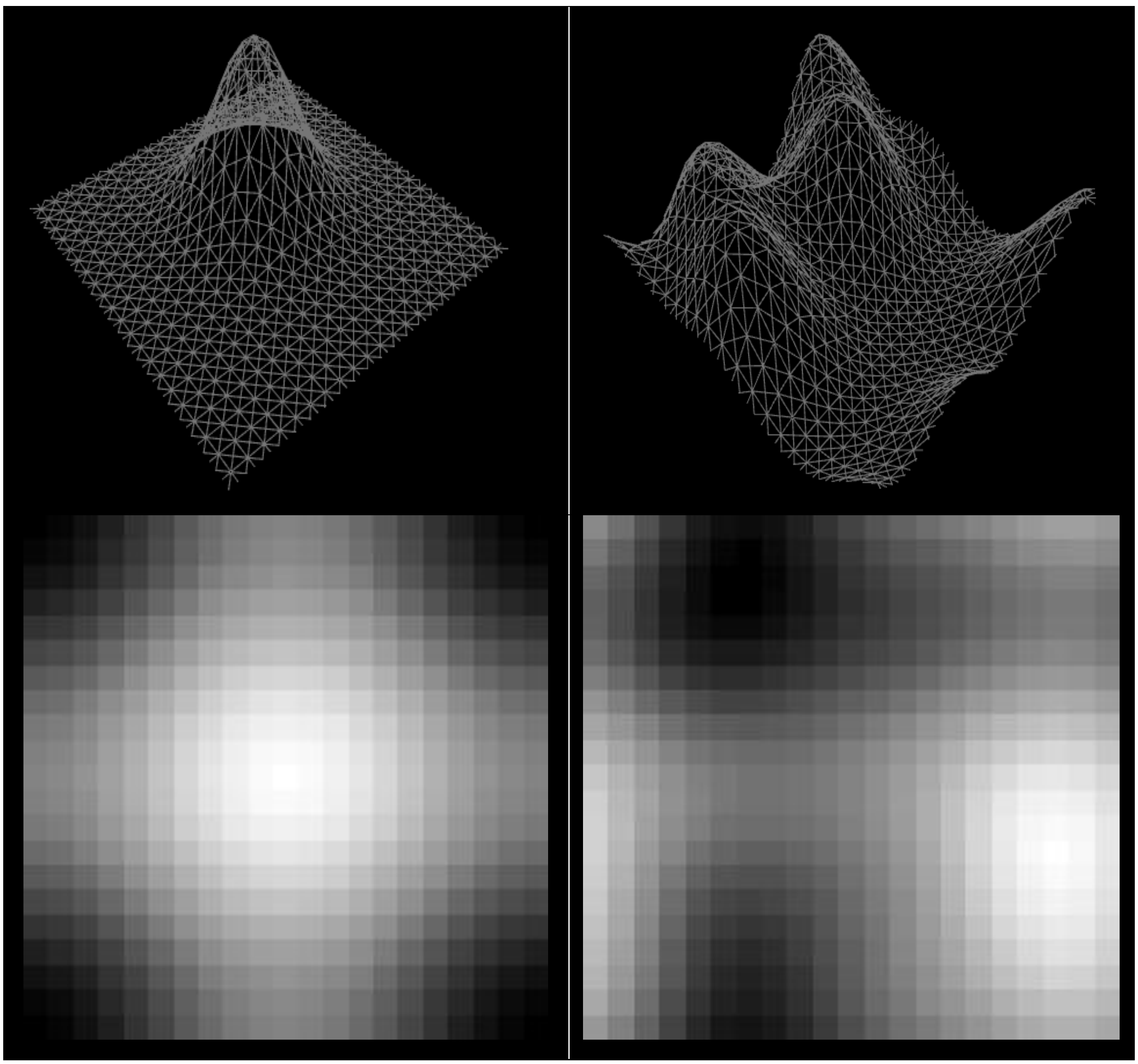


Figure 3.14 C^{2}D Design Landscape for $N = 1$ and $K = 0$ (left) and $N = 4$ and $K = 2$ (right)

The C²D model implements these concepts by implementing each of the three major regions for K separately, including the minimally rugged case $K = 0$, the intermediate cases of $0 \geq K < N - 1$, and the maximally rugged case of $K = N - 1$.

- In the case of $K = 0$ the smoothness of the landscape remains its highest ($S^* = 1$), *i.e.* the randomly assigned fitness values share fitness values across the entire landscape. This is the result of the fact that each design parameter contribution to a particular functional requirement either makes the fitness either higher or lower based on its one of two possible states. This case represents the absence of interdependencies in a design; because of this absence, the landscape contains a single attractive global optimum. As a result, this landscape ensures that any suboptimal design approach lies on a connected pathway to the global optimum because sequential changes to of the suboptimal design contributions will lead to a final single best value. This fitness optimum, as discussed by Kauffmann (1993), shares the same expected level of fitness of approximately 0.66 regardless of the number of functional requirements N.
- In the case of $0 \geq K < N - 1$ the landscape remains variably correlated with varying smoothness ($0 < S^* < 1$). In order to replicate these landscapes we adapt the generalized relationships from Altenberg (1997) to establish the local optima (cf. Section 3.2.2.1) and tables from Kauffman (1993) to rescale the landscape to the observed fitness values.
- In the case of $K = N - 1$, the interdependencies among functional requirements yield a maximally rugged landscape ($S^* = 0$) where changes to one of the satisficing design parameters yields changes to the fitness of every other functional requirement in the design matrix. As a result, the landscape remains completely uncorrelated and includes a great number of local optima in proportion to the number of functional requirements N, the number of possible states A for the interactions, in our case 2, and the dimensionality of the space D (i.e. the number of accessible neighboring alternatives for each design, formally $N(A - 1)$ describes this dimensionality). The resulting expected number of local optima follows from the relationship $E[opt] = A^N/(D - 1) = 2^N/(N + 1)$. For this case, we generate $E[opt]$ random fitness values according to a normal uniform distribution across the design space. We also apply the tables from Kauffman (1993) to minimize any random variability between runs due to the landscape construction.

3.2.4 SMOOTHNESS IN THE C²D DESIGN LANDSCAPE

The interdependencies between how the $\{DPs\}$ satisfy the $\{FRs\}$ give rise to the relative smoothness or ruggedness of the design landscape. In the C²D framework, we equate the complexity of this relationship and the ruggedness of the landscape to the coupling between design parameters and the functional requirements in the design matrix through the approximation of the discussed NK construct. The C²D method implements the relationships, as discussed in Section 3.3.3, through both the previously deduced relationships from Altenberg (1997) and the table values from Kauffman (1993), as well as through an approximating landscape smoothness factor $S^* \ \{ \ s.t. \ 0 \leq S^* \leq 1\}$. This factor represents a scale factor for the repeated averaging of the design landscape through, *i.e.* each design location averages its fitness with the surrounding neighborhood S^* number of times. This smoothness approximation relates the quantity and strength of interactions in the design matrix according to the following equation (assuming a square design matrix):

$$S^* = \ 1 - \frac{\frac{1}{N}(nnz[\boldsymbol{A}] - f)}{N - 1} = \ 1 - \frac{K}{(N-1)} = \ 1 - \frac{\frac{E}{V}}{(V-1)} \tag{3.9}$$

$$K = (1 - S^*)(N - 1) = \left(\frac{1}{N}(nnz[\ \boldsymbol{A}] - f)\ \right) = \frac{E}{V} \tag{3.10}$$

$Where$:

N the number of functional requirements, *i.e.* genes of design

f the number of design parameters, *i.e.* fitness components of design

nnz total nonzero design elements in the design matrix $[\boldsymbol{A}]$, *i.e.* $\sum a_{ij}$

K the interdependencies between FRs in the design matrix $[\boldsymbol{A}]$

V the number of vertices

E the number of edges j to other vertices i, *i.e.* $\sum a_{ij} - f$

The maximum smoothness factor of $S^* = 1$ corresponds to a $K = 0$ minimally rugged landscape and the minimum smoothness factor of $S^* = 0$ corresponds to a $K = N - 1$ maximally rugged landscape. This smoothness factor relates back to the epistasis of the landscape, K, variable vis-à-vis the relationship seen in equation (3.9-3.10) above. As seen by the proposed equation (3.10), this approach allows for fractional epistatic relationships for K. We can also include a weighting factor for the incorporation of additional information into the equations such as sensitivities between individual functional requirements and design parameters. Although the current C^2D framework assumes no specific information relative to these sensitivities, the use of these weighting factors could allow for the further reconciliation of the C^2D approach to axiomatic design approaches. The described framework focuses on the structural complexity of the design space through the discussed NK approximation construct and the behaviors of decision-making agents, designers, exploring this space. We now apply these concepts to demonstrate the differences between coupled systems and to physical design examples to illuminate how these pieces fit together.

3.2.5 SAMPLE DESIGN APPLICATIONS

We have shown that relating the design matrix $[A]$ to the NK model provides insight into the relative complexity of various design approaches given by $[A]$. In the ideal design case where the functional requirements remain independent of the design parameters (i.e. the design matrix remains diagonal or triangular) the landscape follows a simple additive model; however, outside of this instance coupling (i.e. interactions K) between the requirements in the design gives rise to a rugged theoretical design landscape.[29] The NK model construct allows the C^2D model to explore how these differences in structuring of the design matrix influences the fitness of a design approach. In the conceptual phase of design, often the search of the design space has limited a-priori understanding of the landscape. In the absence of this additional information, such as information regarding the exact underlying design sensitivities, the structuring and a loose understanding of the casual relationships in the design space provides insights into the relative value and achievability of competing design approaches. Interestingly, even well understood requirements and designs that are commonplace suffer from many design inefficiencies and possible interdependencies. Designers often fail in fully anticipating the relationships between

[29] In design, we have seen how the structuring of requirements in a square design structure matrix (DSM) can give rise to complexity. However, DSMs can also come in varying structures to include fat matrices (i.e. fewer rows than columns often resulting in redundant designs) and skinny matrices (i.e. fewer columns than rows often resulting in coupled designs). These asymmetrical DSMs, representing the underling dependencies between the satisficing physical form and required functions of an engineering design, result in dependent relationships that drive design complexity. These sometimes-unnecessary couplings increase system complexity and unnecessary redundancies that increase the information content of design and ultimately its manufacturing costs. Appendix L provides an example of how the structuring of these designs can drive the ruggedness of the landscape. For these instances, we replace N in the above equation (3.10) with the lower of the $n \; x \; m$ dimension for the design matrix.

variables (resulting in unexpected dependencies between design elements) and their influence. The search process (i.e. problem solving) of this design space lies the heart of the design process and represents the process of gradually gaining information about the design space through its exploration. We compare the C^{2}D technique for mapping out this design space using an example from the axiomatic design literature (Suh 1990). We use the example of the design of the water faucet, as discussed by Norman (1990) and Suh (1990). In particular, we use the example of a water faucet to illustrate the benchmarking comparison value of the C^{2}D method.

In the example of the common two-handled water faucet, each handle controls the flow rate of hot water and cold water independently. However, this design remains coupled, and according to the principles of Axiomatic design, this approach for creating a water faucet is inefficient. The need from the user, translated into functional requirements, is the ability to control the overall flow rate and overall temperature coming from the sprout, not to control the flow of cold water and the flow of hot water. Interestingly, the inefficiencies introduced by this two-handled faucet design also results in inefficient use of water and tangible waste of roughly to two-liters per day per person using a two-handled faucet. This waste results from the user trying to obtain the right temperature and flow for the water. When translating this waste to half the population of the United States, *i.e.* a rough estimate of households with two-handled faucets, this waste corresponds to over 300 thousand cubic meters of water waste a day. Tables 3.4-3.5 demonstrates this example, where the requirements for a faucet include controlling the water temperature T and the water flow rate $\dot{Q}$ from the faucet. Axiomatically, an ideal solution for the design of the faucet would result in the independent control of the flow from the temperature of the water from the faucet. In addition to preserving independence, in order to reduce the probability of part failure, the designer would also seek to minimize the information content of the design from requiring two design objects (e.g. separate knobs) into one movable part, such as a singular handle with two degrees of freedom where each degree of movement satisfies a design parameter independently.[30]

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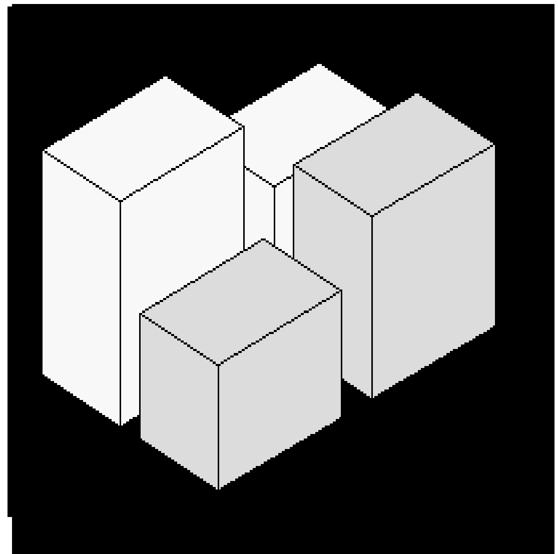
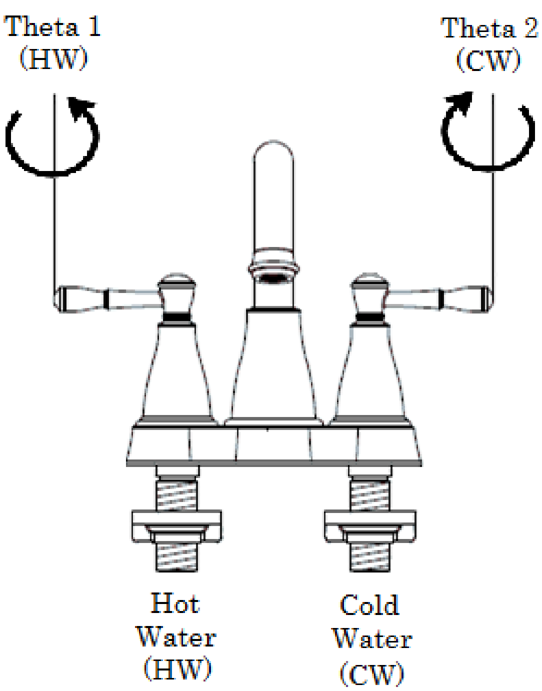
[30] From a systems perspective, the process of design often occurs at multiple levels of hierarchy. The axiomatic design approach remains true to a multi-hierarchical view of design for relating the functional requirements to the design parameters. For example, FRs may actually decompose further (e.g. $FR_1 \rightarrow FR_{11}, FR_{12}$) into several lower level functional requirements and associated DPs (e.g. $DP_1 \rightarrow DP_{11}, DP_{12}$) leading to a larger multi-scale design matrix. In these larger systems, the same approach described above holds true. In the following example, we use simple top-level design requirements and design parameters. Appendix M also expands on the approach demonstrated in the example by providing a possible initial framework for incorporating the sensitivities of the design elements. Appendix N provides an additional design example for an uncoupled light switch design.

Table 3.11 Two-Handled Faucet, Coupled Design Example

A common version of the faucet design includes employing separate knobs to control the flow rate of hot water (HW) and to control the flow rate of cold water (CW). Although the number of DPs equals the number of FRs, the design violates the independence axiom as the satisficing design parameters controlling temperature and flow rate depend on one another. The landscape clearly shows the possibility for the development of suboptimal designs because of this conceptual design approach given by $[A]$.



Location		Fitness Values		Average
$\dot{Q}$	T	θ_1	θ_2	$\frac{1}{n}\sum_{i=n}^{n} i$
0	0	0.32	0.45	0.39
0	1	0.73	0.24	0.48
1	0	0.49	0.69	0.59
1	1	0.23	0.43	0.33



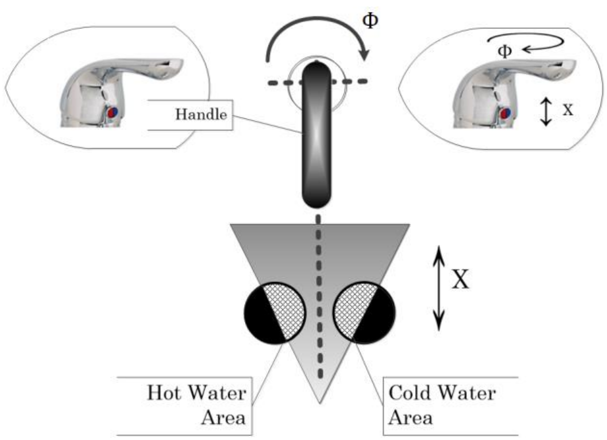
$$[A] \rightarrow \begin{Bmatrix} \dot{Q} \\ T \end{Bmatrix} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{Bmatrix} \theta_1 \\ \theta_2 \end{Bmatrix}$$

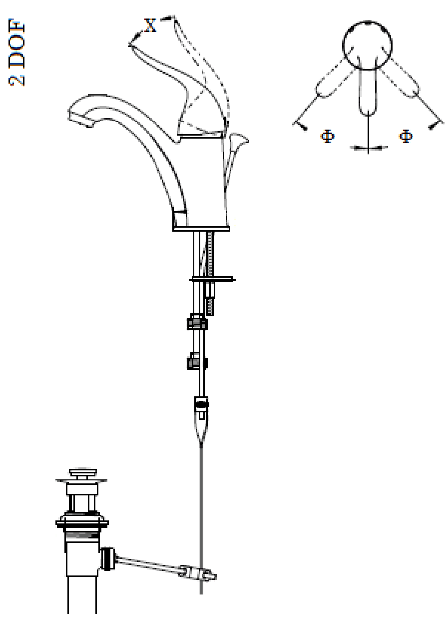
$\dot{Q} = a_{11}\theta_1 + a_{12}\theta_2 \qquad T = a_{21}\theta_1 + a_{22}\theta_2$

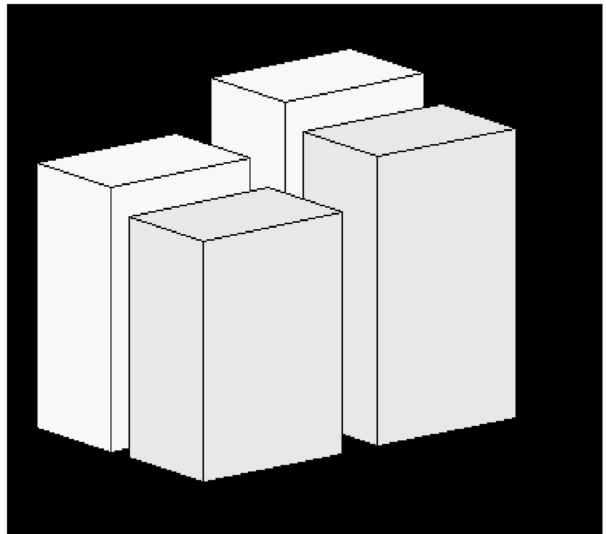
$S^* = 0 \qquad N = 2 \qquad K = N - 1 = 1$

Table 3.12 Single-Handled Faucet, Uncoupled Design Example

An uncoupled version of the design includes using one knob to control independently both the flow rate and the temperature. In this design, the horizontal plane for the handle controls temperature and the vertical plane for the handle controls flow rate; as a result, the design maintains independence while minimizing the design to one handle.







Location		Fitness Values		Average
$\dot{Q}$	T	X	Φ	$\frac{1}{n}\sum_{i=n}^{n} i$
0	0	0.6	0.4	0.5
0	1	0.6	0.5	0.55
1	0	0.80	0.4	0.60
1	1	0.80	0.5	0.65

$$[A] \rightarrow \begin{Bmatrix} \dot{Q} \\ T \end{Bmatrix} = \begin{bmatrix} a_{11} & 0 \\ 0 & a_{22} \end{bmatrix} \begin{Bmatrix} X \\ \Phi \end{Bmatrix}$$

$$\dot{Q} = a_{11}X \qquad T = a_{22}\Phi$$

$$S^* = 1 \qquad N = 2 \qquad K = 0$$

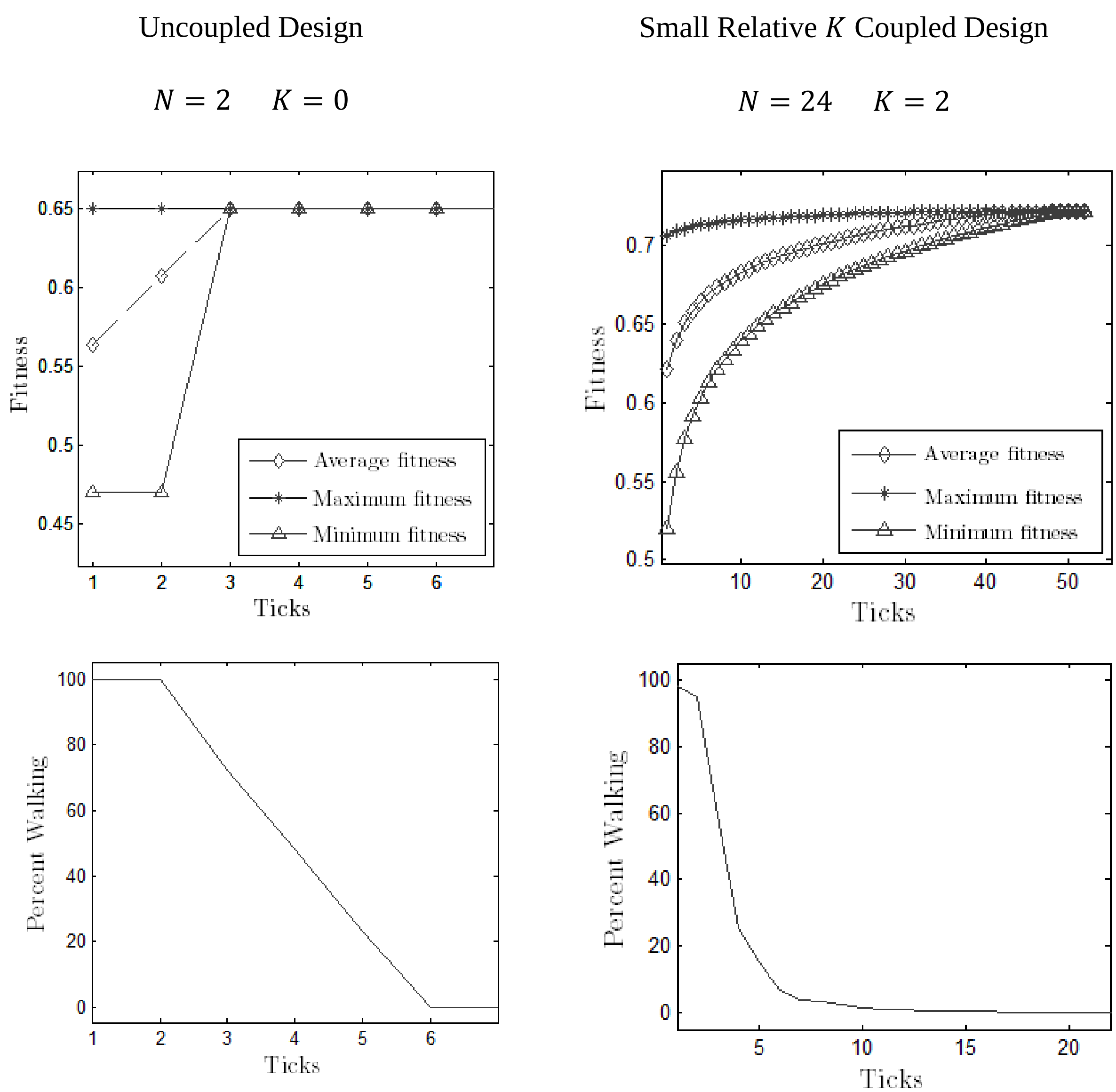


Figure 3.15 Role of N and K in Search Performance. Variations in the number of entities (i.e. requirement) N and the level of interdependencies among these entities K drive unique landscapes, each with their own associated search challenges. The above example uses 100 independent agents over 100 runs. We provide these examples to highlight that, interestingly, small values of interaction tend to provide greater fitness to a design landscape over no interaction; this advantage quickly disappears, as the design becomes increasingly complex ultimately leading to the complexity catastrophe discussed in Chapter 2. For completely uncoupled designs ($K = 0$), the design fitness averages, regardless of the value for N, over multiple runs to 0.66 approximately. In a highly rugged landscape, the design fitness for the landscape averages, with increasing values for N, over multiple runs to 0.50, resulting in the complexity catastrophe. Additionally, design agents, depending on their strategy, quickly migrate to local optima, leaving them caught. Design-teams maybe concerned with either maximizing their performance, *i.e.* final fitness value, or meeting the minimum performance characteristics required in a design in order to get to market quickly, *i.e.* minimizing the design-time. Each of these objectives corresponds to different strategies. We examine these strategies relative to the collaborative team dynamics discussed.

At the heart of the C^2D framework is the collaborative relationships that exist between designers as they explore a complex problem space defined by the design landscape discussed. Introducing these agents onto theoretical design landscapes provides the ability for the experimenter to explore strategies that improve the performance of the design-teams, *i.e.* the ability of these teams to navigate these design landscapes, under various conditions of uncertainty in a design approach.[31] In the above example in Figure 3.15, we introduce multiple general agents on the surface of randomly generated NK design landscapes. We allow the agents to explore the landscapes multiple times, averaging the maximum values, the mean values, and the minimum values for the fitness of these agents. In these runs, the agents perform the basic hill climbing strategy in order to find new optima by exploring each of their north, south, east, and west neighbors. We allow these agents to perform long jumps in the event that they reach suboptimal design points. Interestingly, as noted by Kauffman (1993) due to the nature of the NK landscape, very low levels of K (i.e. $K < 4$) improve the fitness of the landscape when compared to that of $K = 0$ as seen in Figure 3.15. However, by imposing the requirement in the C^2D model for designers to converge on a single design solution (while simultaneously providing the team the tools to break free from local optima through the adoption of new team members) we depart from traditional NK search optimization inquiries. For example, certain strategies for exploring highly uncorrelated landscapes, where design elements share many interdependencies, result in greater search times in the C^2D model compared to the similarly highly correlated landscapes in the NK approach. This is a result of the various designers having to search each design location in order to find sufficient fitness on the landscape. Most importantly, our approach departs from traditional optimization-based inquiries of these complex landscapes through the focus on the collaborative nature of design and the design-team; it is the human-like agent-based designer with its goals, rules, percepts, actions that underpins this analysis.

[31] Earlier in Chapter 2, we discussed the relationship between uncertainty and complexity. Suh (1990) defines complexity in terms of the uncertainty in meeting design requirements. Similarly, we use a theoretical design landscape to provide insight into the ability of designers to meet design requirements; however, we focus predominately on the given structural complexity of a design approach to provide a generalizable framework across various designs. In Appendix M, we provide a note on how we can build on these concepts by using design sensitivities between design requirements and design parameters to provide greater clarity into its application for designs where partial knowledge exists about the relationships between particular requirements and parameters.

3.3 Dynamics of Designer Collaborations

Nearly all complex engineered systems today result from the definitional activities between the interactions of multiple collaborative designers. The word *collaboration* derives from the Latin combination of '*laborare'* and '*com'* to mean laboring together (Vreede and Briggs 2005). We use collaboration similarly to mean the shared effort of engineering designers. Current techniques for managing the shared labor of engineering designers, including managing their associated collaborative dynamics, result in expensive and time-consuming processes. Often these design processes result in the failure to incorporate important life-cycle considerations, while also limiting the creativity in the design process. The difficulty in design increasingly forces incremental modifications to sub-optimal design solutions as opposed to exploring the possible full range of solution (Klein et al. 2003). At its core, these design collaborations represent a form of negotiation between multiple stakeholders concerning the elements of a design (Sycara 1991; Scott 1998; Kusiak 1999; Klein et al. 2003; Lewis, Chen, and Schmidt 2006). As seen earlier in Section 3.2, the design matrix $[A]$ encompasses the key parameters or issues of concern in the negotiation between designers. Consider designs from aerospace engineering, such as satellite design, where strong interdependencies commonly exist between the functional requirements and design parameters.

These interdependencies require on-going and iterative design trades between responsible engineers and designers in order to establish a balanced design that meets an overall system goal or objective; more specifically, these trades commonly mean designers must trade their system allocations with regard to mass, power, geometric footprint, and, among others, thermal margins in order to achieve their subsystem performance objectives. These decisions and choices available to the designers often remain highly coupled and interdependent. We described the resulting multi-dimensional space of possible negotiation outcomes between designers as the C^2D *design space* using the NK landscape generation approach described previously.

However, these negotiations or trades between designers can often result in agency costs and introduce difficulties under traditional rational models of decision-making; the decision-making processes in design share many characteristics in common to the prisoner dilemma. For example, aiding fellow designers by giving back to the system margin can commonly leave the concessionary designer in a degraded performance state. This system margin can also often represent a form of mitigation against uncertainty in a design. As a result, designers may act rationally to preserve and bulk up their individual margins, even if their cooperation with other designers could lead to greater performance for themselves or the overall design. When these actions negatively influence the overall design performance, *i.e.* resulting in sub-optimality, due to allocative inefficiencies in the distribution of system margins, we label this event as an agency cost. Implicit in these parallels is the lack of a unified rational model for distributed or collaborative decision-making. We look at how to overcome this agency costs and lack of generalizable decision-making model by using mediating influences, such as the incorporation of highly diverse newcomers and the application of technical management pressure required to drive a team toward consensus. These newcomers, if allowed to join, offer the team a new perspective and may provide a radically new possibility for exploration. These team-formation parameters, found by Guimerà et al. (2005) to drive collaborative team performance, provide the underpinning of how the designers search the design-landscape and overcome sub-optimality. Performance in C^2D arises from the effectiveness of the DAU in its searching and decision-making processes. These processes follow a combination of governing rules for the individual designer-agent and the collective collaboration based on the concepts of naturalistic decision-making as described by Dougherty, Ambler, and Triantis (2014) and as stated previously (cf. Chapter 2, Section 2.4).

Many of the complex designer-artifact-user systems, such as those used in the creation of aircraft, result in millions of design issues, must also deal with the difficulties induced from the sheer volume of decision-making exchanges between hundreds to thousands of collaborative participants (Klein et al. 2003).[32] For designers exploring immensely complex design spaces, this often means looking for designs that meet performance objectives; moreover, in principle this leaves designers striving to find designs that are incrementally better than other alternatives. As a result, although we can view the *goal* of the design process as finding a theoretical global maxima, in reality optimality is often abandoned in favor of ‘good enough’ (Klein et al. 2003). Given the real-world limitations, implicit in the previous statement, this often means the designer must work on a comparative basis. Consequently, we use, in part, the hill climbing algorithm as an essential tool in the search of fitness on the *design landscape*. However, as discussed so far, the design

[32] Although we speak of design participants in the context of designers on a singular design-team for simplicity, the C^2D approach remains inclusive to the analogy of the agents representing teams or organizations representing design subsystems.

landscapes can often represent complex non-linear spaces with many optima of varying fitness levels. Hill climbing alone would leave the design-team stuck at multiple potential design solutions in these instances. As such, we look at multiple strategies and approaches for overcoming and mitigating complex design landscape in the subsequent section. In order to explore the nature and dynamics of these collaborative design-teams, themselves complex adaptive systems, we discuss them in terms of the following:

- Design-team parameters and dynamics
- Design-team formation procedures
- Individual decision-making rules in C^2D
- Collaborative decision-making rules in C^2D
- Search strategies for design

3.3.1 Design-team Parameters and Dynamics

We describe the overall collaborative design-team as the all-encompassing collective of newly assembled collaborating designers and established teammates involved in a design activity. As a design activity progresses in the C^2D approach, a newly assembled design-team forms to engage the design activities at hand. These newly formed design-teams join and operate within the context of a larger supporting network of collaborators (i.e. the collaborative design-team). These networks comprise incumbent and experienced designers who were already once participants of an assembled design-team. This collaboration network provides a store of experiential design knowledge accessible through future collaborations on a design-team. The way that members of the design-team embed themselves within these larger collaborative networks dictates their ability to access these stores of knowledge; similarly, design-teams formed by large and disparate sets of collaborators draw from a more diverse reservoir of knowledge (Guimerà et al. 2005).

The design-team uses links to represent their current and previous collaborations. We use various colored links in the newly assembled design-team to differentiate the nature of the collaboration. For example, we use blue links to represent collaborations between two newcomers, we use red links to represent collaborations repeated more than once, we use yellow links to represent a collaboration between two incumbents, and finally, we use green links to represent a collaboration between a newcomer and an incumbent. These links and their quantities provide insights into the nature of the team and its team-dynamics. For example, an overabundance of yellow links may indicate a lack of diversity in ideas or experience. To correct this, a team would work to improve the nature of these relationships in future collaborations. Similarly, the C^2D framework allows for this increase by providing parameterized controls for the team-formation dynamics of the DAU.

The mechanisms responsible for the formation of these design-teams follows from several key governing parameters from the literature (cf. Chapter 2, Section 2.4). We explore how each of these parameters individually govern the design-team while also providing the associative inferences design in general. We build on the suggested parameters from the literature by incorporating a diversity parameter to describe the variety among designers and their approaches. These parameters include:

- the newly assembled team size (n);
- the probability of incorporating a newcomer (p);
- the probability of repeating a collaboration (q);
- the diversity of newcomers (m); and,
- the maximum downtime for a collaboration newcomer (mdt) and natural selection

3.3.1.1 Newly Assembled Team Size (n)

The newly assembled team size given by n represents the number of core design-team members responsible for executing and coordinating the current design activities. In engineering design, the number of team members typically scales according to the challenge and difficulty of the design task. Sometimes this scaling occurs due to external pressure exerted by technical management to complete a design and decrease the time to market. Successful design-teams and design collaborations must evolve toward a size large enough to satisfy the required design specialties and large enough to ensure the effective division of labor among teammates while remaining small enough to avoid the overwhelming costs associated with design coordination. In our analytical approach, we maintain a constant team-size; however, the currently implemented C^2D model allows for the dynamic variation of all design-team formation parameters.

We keep this value constant as we assume that, implicit to its evolutionary dynamic, an optimal design-team size exists for each given design based on its intricacies and complexity. In implementation, we keep this value constant during each individual simulation; however, we explore it influence by varying the C^2D model seed and team size over multiple runs and comparing the resulting performance values for the different values for team-size. New design-teams form at each increment of time. The addition of newcomers to these teams grows the design collaboration network. We envision this larger collaborative network, as a growing store of collaboration potential with varying diversity characteristics (as seen in the variable placement of collaboration agents in the design landscape).[33] From an engineering design perspective, team size remains relatively small during the period of conceptual design (unlike the detailed design phases) at the center of the C^2D framework.

The size of a team and its overall collaboration network can have major ramifications on the time it takes to come to a final design selection. The association between the size of a team and its performance represents a balance between the gains of finding more optima quickly with a larger team and the cost of having more collaborative stakeholders involved in the consensus and coordination processes of design. As design opportunities and solutions grow in number and gain prominence amongst contingents of the overall collaboration, the design negotiation process sometimes results in a protracted affair. We introduce the concept of technical management pressure, a strategy discussed later in Section 3.3.4, to force the DAU to come to consensus. This technical management pressure corresponds to an increased penalty in the natural selection underpinning the C^2D model. Many questions of interest concerning team-dynamics in business and academic communities are tightly associated with team size, typically these questions center on the causative relationship or association of team size to team effectiveness. For instance, adding more designers creates many new pathways of possible interactions proportional asymptotically to the quantity of designers n^2, following from Metcalfe's law of network efforts. Because of the growing number of necessary coordination avenues, the team size parameter remains a critical parameter in exploring the effect of team size on coordination and its potential deleterious

[33] The team-formation procedure ensures the growth of the collaboration based on its parameterization to a natural equilibrium. This equilibrium depends also in part on the expiration of collaborative members discussed as part of the maximum downtime parameter. The procedure repeats at each increment of time (*i.e.* at each tick the designers enter the larger collaboration network or collaboration pool). However, depending on the probabilistic outcome of the team selection procedure design-team members from previous increments of time may 'in effect' remain on the team into the following increment of time if again chosen to collaborate. Each design-team member has an effective turnover potential at each increment of time based on the team formation parameters, as well as time t in ticks. This exploration for the turnover probability $p_{TO} = f(p, q, n, t) \approx 1 - (2q(1-p)/t(1-q)(n^2-n))$ remains an ongoing area of research; the addition of a Bayesian approach would more accurately capture this probability for the given modelling approach over time.

influence. Similarly, this comparison provides insights into the possible occurrence of "social loafing," a phenomenon in social psychology where team members exert less effort to achieve a goal when working in a larger team compared to when they work in small teams or alone (Karau and Kipling 1993; Gilovich, Keltner, and Nisbett 2010). Supporting this line of team size inquiry, we cite the well-known Ringlemann rope-pull study that measured the force exerted by individuals and groups of varying team sizes when pulling a rope. The study found the tendency for individual members of a group is to become increasingly less productive as the size of their group increases (Forsyth 2009). We attempt to validate similarly a theoretical relationship between the complexity of a task K and the existence of an optimal team size based on the resulting performance of a team as part of Hypothesis 4 discussed earlier in Chapter 1, Section 1.2.

3.3.1.2 Probability of Incorporating a Newcomer (p)

New designers joining these current design-teams do so with a probability given by the p parameter. This parameter represents the need, desire, and willingness of the design-team members to try something new. We define these new designers (i.e. newcomers to the design project) as completely new to the collaboration (i.e. external from the current collaboration); it is through these designers that the design-team gains the potential for increased diversity. From an algorithmic perspective, these new agents provide long-jump opportunities in the exploration of the design landscape. For engineering design organizations, this incorporation would often represent either the recruitment of a new individual, whether a new hire or, more likely, a new designer added from elsewhere in an organization (a common technique for matrix organizations). The individual decisions of each current design-team member determines whether to incorporate a brand new designer with probability p or to maintain the status-quo by instead adding an existing designer from the collaboration. For example, in the event that $p = 0$ the team will only comprise current or existing team member from the larger collaboration. However, in the event that $p = 1$ the team would constantly assemble teams made entirely of designers from outside of the collaboration. The dominance of these more inexperienced designers (relative to the tasks of the design) tends to extend the searches of the design landscape, depending on the relatively complexity and intricacies of the design, as the team loses its anchoring to the richer knowledge and experiences of its larger collaborative network.

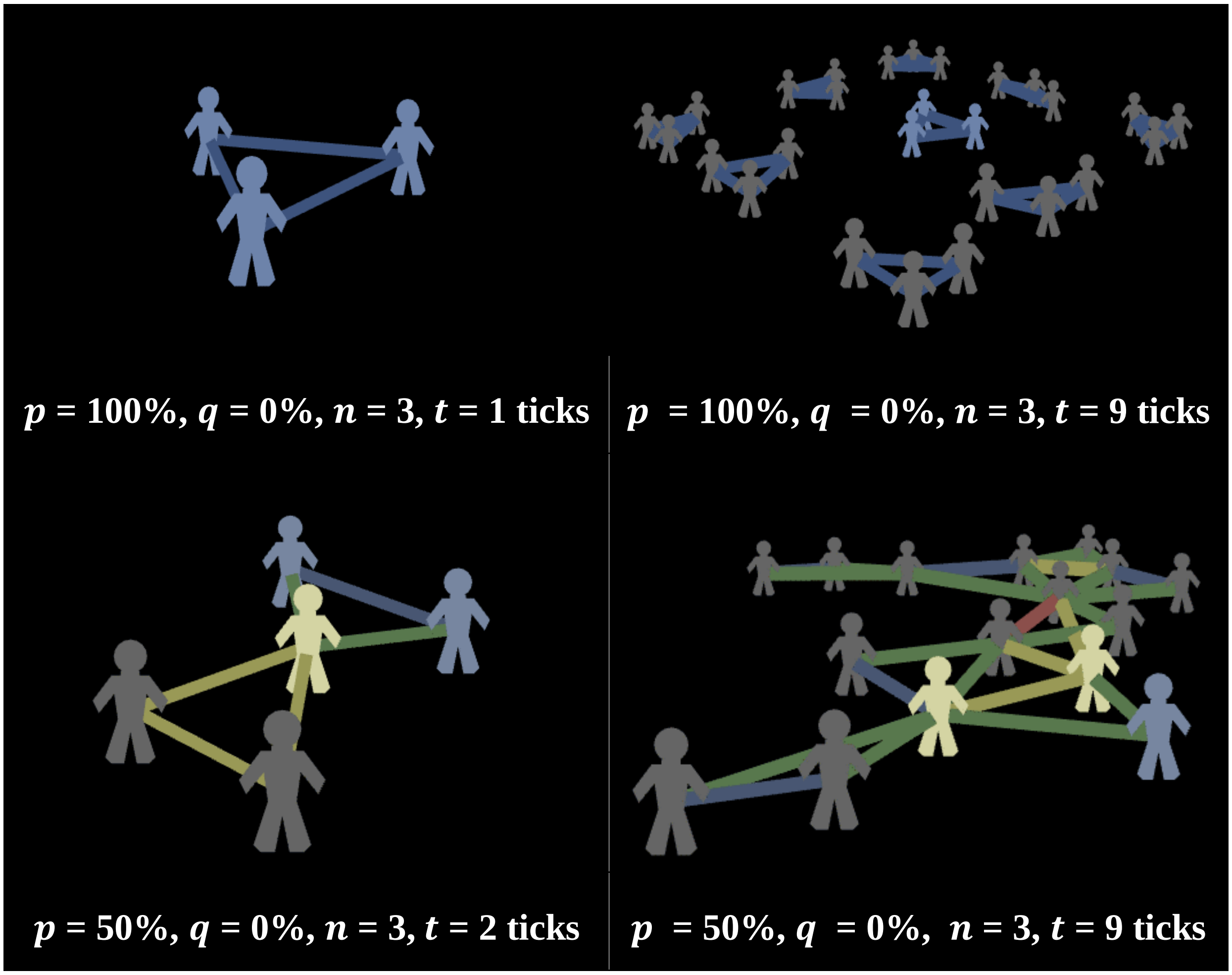


Figure 3.16 Likelihood of Incorporating a Newcomer and its Impact on the DAU Network Structure. We demonstrate the role of the parameter p, the probability of incorporating a newcomer, by showing the formation of teams and their emerging network structures at various increments of time, as measured in the model through ticks. The figure on the top left demonstrates the initial team at the first tick. It form with n team members. As the probability of calling a newcomer remains constant at $p = 100\%$, each subsequent team forms a similar team. The figure on the right demonstrates these subsequent teams at tick nine. Because of this parameterization, a new team of newcomers joins the collaboration at every tick, making the collaboration grow by n at each tick. The figure on the bottom left demonstrates the case where the team incorporates a newcomer with a probability $p = 50\%$ at tick two. After the initial team forms on the first tick, the subsequent tick results in a team that has two newcomers and one incumbent. We gray out non-team members for purposes of the illustration. We select the one incumbent from the overall incumbent pool that, which as of tick two in this scenario includes the existing three incumbents. The number of designers involved in this collaboration, as a result, grows from the initial team size of three to a total collaboration of size five. In the bottom right figure, we allow this random draw of newcomers to continue over the same nine ticks as done above. In comparison to the parameterization alternative discussed, the resulting collaboration remains fully connected as a result. In these figure we demonstrate the dynamic of team-formation and the probability of incorporating a newcomer on a team alone, there are no maximum-downtime or fitness considerations as discussed later in this section. In the next section, we examine the role of repeating a collaboration q as opposed to continually drawing at random from the overall collaboration pool.

As the design-team size n remains constant, the human resources and engineering managers must work to create a balanced design-team of experienced and inexperienced but appropriately diverse designers. Individual designers commonly contribute to an idea and propel the design forward only for limited periods or bursts. In other words, each designer can often only take a design so far based on his or her unique experiences, background, and the aspects of the design for which they have responsibility. Therefore, the exploration of the design landscape requires the inclusion of new design-team members as these newcomers provide the design-team a different set of ideas, skills, and resources from which to work. This continual influx of new ideas enables the continual exploration of the design landscape, allowing for the evaluation of multiple diverse design approaches. The degree of differentiation between these newcomers represents an aspect of the diversity. Although we keep the probability of incorporating a newcomer p constant in the analysis portion of this research, we introduce and dynamically vary a modifying factor to the location of newcomers through this concept of diversity.[34]

As the team incorporates new team members over time, the overall collaboration network grows in size as past team members form an underlying network of possible collaborative team members. This network of past collaborations often yields a large underlying connected network, which Guimerà et al. (2005) refers to as the emergence of an "invisible college" within the collaboration. However, the C^2D model not only measures the percent of designers connected to this "invisible college," it also allows for the broader continued exploration of other network factors (e.g. clustering, connectedness) and their relationships to design performance.

Similar to the questions surrounding team size, the questions surrounding the incorporation of newcomers represent central concerns in the study of group dynamics. Although the inclusion of newcomers can certainly aid the search of a design landscape by promoting creativity, it can also similarly promote conflict and miscommunication (Granovetter 1973; Larson et al. 1996; Edmonson 1999; Reagans and Zuckerman 2001; Jehn and Mannix 2001; Burt 2004; Guimerà et al. 2005). We test for this balanced relationship in Hypothesis 2 by looking for a U-type relationship between the final fitness of the design-team and the probability of including

[34] The current implementation for C^2D allows for the dynamic ramping for both p and q; however, its benefits in initial runs of the simulation remained limited and the ramping of these parameters provided little to no additional benefit when compared to other strategies.

newcomers. Similarly, in Hypothesis 5 we test for general relationships, specifically a proportional relationship, between search times and the probability of including newcomers (cf. Chapter 1, Section 1.2).

3.3.1.3 Probability of Repeating a Collaboration (q)

If instead of selecting a newcomer with which to collaborate a design-team member selects an incumbent, *i.e.* designers already part of the collaborative network, the design-team member must then also decide with what type of incumbent to collaborate. This occurrence occurs with a probability of $1 - p$. In this event Z, the designer-team member can decide to repeat a previous collaboration of a current team member or to tap the wider knowledge of the collaborative network through one of its designers. In the event Q, the design-team member chooses to repeat a collaboration of an existing design-team member with probability q. Similarly, the design-team member can instead choose to collaborate with a previous team member now embedded in the larger collaboration network with a probability $1 - q$. We can also express the likelihood of these events $Q$and Z occurring as a conditional probability in equation (3.11) and as a joint probability in equation (3.12), which follows:

$$P(Q|Z) = \frac{P(Q,Z)}{P(Z)} = \frac{P(Q|Z)P(Z)}{P(Z)} = q \tag{3.11}$$

$$P(Q,Z) = P(Q|Z)P(Z) = q * (1 - p) = q - qp \tag{3.12}$$

Repeating a collaboration with a probability q entails considering the past collaborations of a randomly selected member of the design-team, *i.e.* assessing the accessible members of the collaborative network. The existence of links directly to a design-team member determines this accessibility of an incumbent design-team member. The accessibility of these collaborators and existence of links depends largely on the history of team assemblies and, as a result, where the selected agent now finds itself in the larger collaboration. If there are no accessible previous collaborative design-team members, the design-team member must collaborate with a member of the overall collaborative network at random. Similarly, in the $1 - q$ case a member of the design-team decides to tap into the “invisible college” by collaborating with any designer at random, potentially gaining new and relevant skills for the given stage of the design.

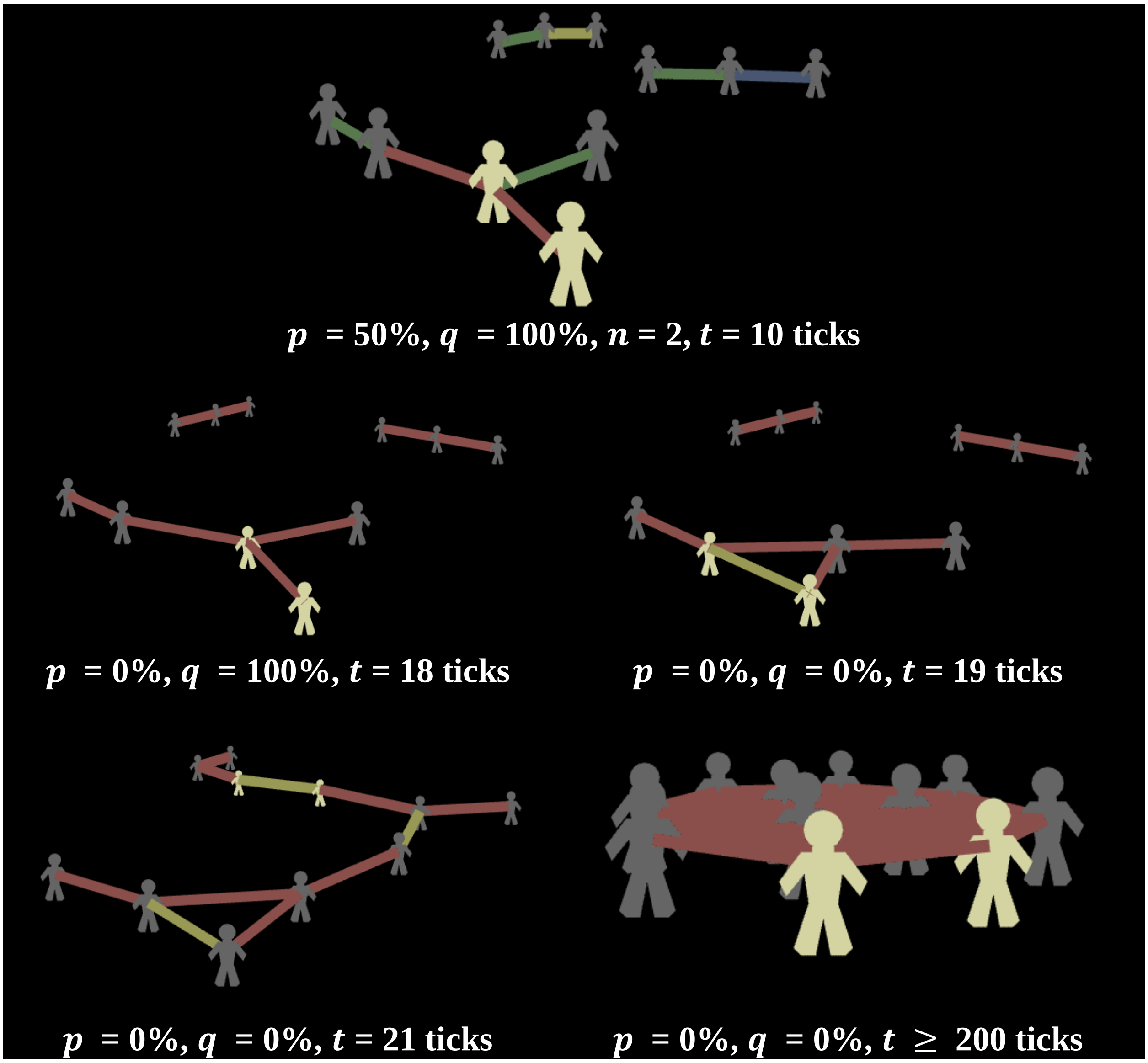


Figure 3.17 Propensity to Repeat Collaborations and its Impact on the DAU Network Structure. The influence of repeated collaborations and its corresponding design-team formation parameter q surfaces in the figure shown above. The figure on the top represents an initial team structure and parameterization; however, without newcomers and $q = 100\%$ each collaborative agent only can collaborate with accessible collaborators regardless of how long the team collaborates. As a result, this condition leaves the three population of designers continually disconnected. However, by doing the reverse and setting $q = 0$ the current design-team members can select any member from the overall collaborative network. As before, we gray out non-team members for purposes of the illustration. If allowed to continue under these conditions, the collaboration quickly establishes links between each designer and every other designer, the number of links follow from $n(n-1)/2$ given by Metcalfe's law. Because of having no newcomers, the collaboration network quickly clusters into a tightly formed singular collaboration group of repeated collaborations as demonstrated in the bottom right, a result that occurs quicker (i.e. in less ticks) in the case of no repeated collaborations versus the case of some repeated collaboration, ceteris paribus. We discuss the relationship between this propensity to repeat collaboration and search times as part of Hypothesis 6 (cf. Chapter 1, Section 1.2).

3.3.1.4 Diversity of Newcomers (m)

Although restraining q can help ensure the diversity of the design-team by limiting the amount of repeated collaborations, this limit on repeated collaboration does not promote diversity through the inclusion of diverse newcomers. The capacity for diversity among newcomers described by m offers a unique opportunity to improve design performance modelling for teams by providing a new approach for expanding the overall collaboration network to new locations on the design landscape. Allowing diverse newcomers provides the capability of the overall design-team collaboration to bring in a new design-team member anywhere on the design landscape depending on the value of m, the maximum distance on the design landscape in patches. In other words, newcomers join the collaboration through a random-normal jump up to m patches away from the selecting design-team member. This jump in C²D occurs on a random heading from the selecting agent. This occurrence also parallels the biological and natural selection paradigm of mutation, specifically of mutagenic distance.

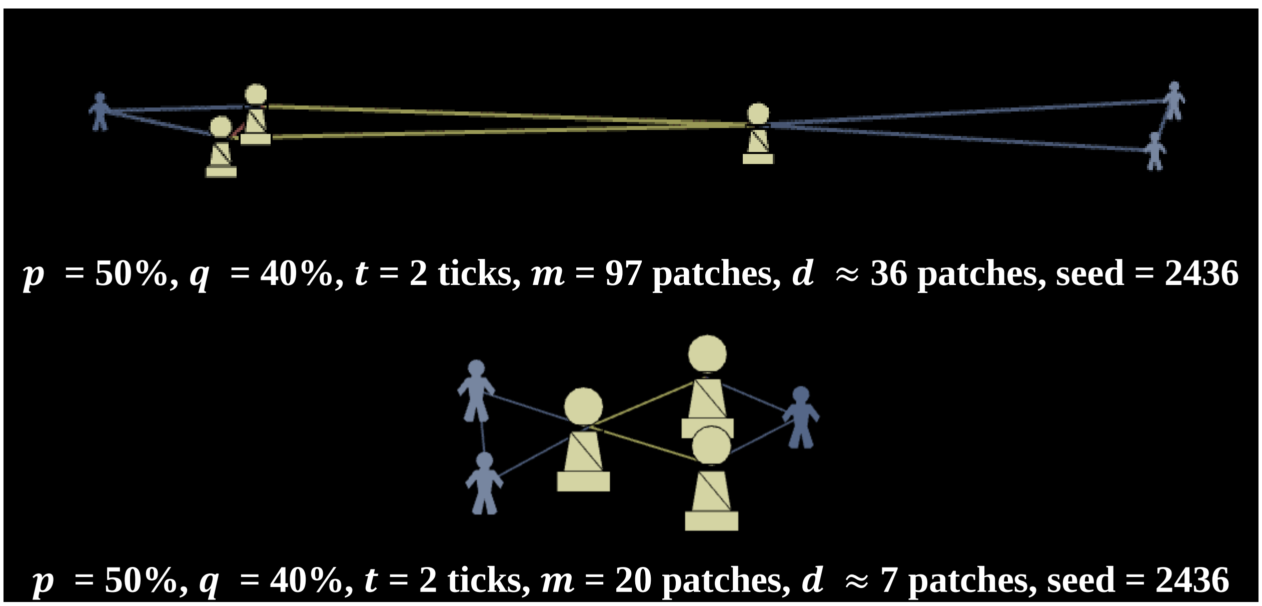


Figure 3.18 Diversity of Newcomers Impact on the DAU Structure. The figures above demonstrate the influence of diversity m on a team structure with a team-size of three. This parameter enables a greater distance d, between newcomers and incumbents and parallels the biological concept of mutagenic distance. This greater distance results in a stretched team covering more of the design landscape; however, this disparity of locations can also create difficulties in bringing the design-team and collaboration to a consensus quickly. This increased coverage of the design landscape can also mean, in highly rugged landscapes, design-team members moving to multiple attracting local optima. Similar to the concept of allopatric speciation in biology where multiple species emerge, in our case design-factions, based on their isolation. In the above figure, we represent the current team at tick two by the pawns, the default convention in the C²D model for highlighting current team members.

Increases in the diversity of the design-team members enables the evolvability of the design-team by increasing its adaptability to the design-landscape. However, this adaptability depends on the characteristics of the design landscape, in particular the ruggedness of the design landscape. With the simple additive landscape case where functional requirements remain independent, the performance characteristics of the design-team remain largely insensitive to the diversity levels. This finding parallels the biological concept of mutational robustness, which describes the occurrence of the same phenotype in a biological entity regardless of the variety of environmental perturbations. We test the relationships between this diversity capacity m to search times and final fitness values in Hypothesis 7 from Chapter 1, Section 1.2 for various levels of complexity in the design landscape.

3.3.1.5 Maximum Downtime for a Collaborator (mdt)

The C^2D framework recognizes and treats the store of possible future collaborations as a perishable commodity. Specifically, each designer c_d of the larger collaboration C when not engaged after a certain period, specified by the maximum downtime (mdt), leaves the larger collaborative network. We specify mdt in terms of ticks in the C^2D model. This represents one way agents leave the collaboration as seen in equation (3.13).

$$downtime \leq mdt \;\; \forall \;\; c_d \; \in C \tag{3.13}$$

We test for relationships between the duration of the maximum downtime and the search times of the design-team as part of Hypothesis 8 from Chapter 1, Section 1.2. As a design-team grows the overall design collaboration size, this parameter helps to ensure that the overall number of collaborators in a design effort comes to a natural equilibrium. We augment this maximum downtime factor to incorporate aspects of management pressure and the natural selection dynamic.

3.3.1.6 Management Pressure (λ_u) and the Role of Natural Selection

The design effort works to establish teams based on its current understanding of the landscape, *i.e.* better ideas and design concepts have a higher probability of promulgating into the future. In nature, the theory of evolution from Darwin (1859) employs natural selection as the mechanism that ensures that biological entities, such as a species or group, with higher fitness out compete less fit biological entities, in turn passing on their desirable fitness characteristics. For an individual, fitness or viability represents a trait that corresponds to whether or not an individual biological entity survived to reproduce or expired prior to reproduction. In the terms of design-teams, the higher performing design-team members, similarly measured by fitness, also have the greatest likelihood of requesting resources and growing the design collaboration. In order to implement the dynamic of natural selection, we do so indirectly by removing unfit designers above a certain age (i.e. underperforming and experienced designers) from the collaboration. This implementation remains consistent with other natural selection agent-based modelling efforts, including the Wilensky (1997) model of the peppered moth (Biston betularia f. carbonaria) based on the case study from Kettlewell (1955). These modelling efforts generally account for natural selection by removing agents whose age exceed a random fitness value; these efforts include the McAvity (2006) NetLogo modelling approach of fitness landscapes. This approach remains consistent with the principles in contemporary evolutionary theory that state organisms less adapted to their environment remain more likely to die having produced fewer offspring, thereby reducing their contribution to the gene pool (Gilbert 2000). In the C^2D implementation for design, a designer c_d with a higher fitness similarly has more opportunities to repeat its participation in the collaboration C and pass its knowledge about the design space onto the next design members. However, we also ensure that these designers have a minimum amount of time before expiring to give them sufficient time to explore its local neighborhood on the design space, analogous to giving new team-members time to overcome an initial learning curve. We implement this natural selection dynamic through the conditions in equation (3.14).

$$\left(f \geq \lambda_u * random\left(f_{objective}\right) \vee age \leq random(f)\right) \forall \; c_d \in C \tag{3.14}$$

Where:

f	fitness of a collaborative designer c_d
λ_u	management pressure, a scaling to the required stopping-fitness
$f_{objective}$	fitness objective value and the required stopping-fitness
age	age of a collaborative designer c_d in the collaboration C

One key differentiation between the biological context and the design-world centers on what drives a required fitness. In the natural world, fluctuations from the environment can exert a pressure that results in the advantage of one species over another, and, in the worst case, the extinction of an unfit biological entity (e.g. species). In design, often management and technical leadership can drive a solution to conclusion, even if prematurely and at the expense of the relative fitness of a final design concept. This exertion of pressure enables a management strategy to increase its selectivity concerning the continued promulgation of design concept into the future via fitness restrictions placed on the participation of design-team members in the collaboration. This management pressure only changes from its default value of one in the event that the analyst employs an associated management strategy.

3.3.1.6.1 Management Pressure and Its Selective Application, A Note

Although we discuss strategies in more detail in section 3.3.5, it is important to discuss how these parameters enable management strategies. In particular, we discuss how the management pressure concept discussed can enable a design manager to help drive the design-team to a final solution. In engineering design, design often goes through several key phases as discussed in Chapter 2, Section 2.1.1. These phases comprise a goal-attainment model for engineering design and included ongoing communication and evaluation activities across discrete phases for task clarification, concept generation, embodiment design, and detailed design. These discrete phases also result in some characteristic patterns of collaborative goal-seeking teams discussed in the literature, to include divergence, convergence, organizing, evaluating, and consensus (Briggs and Vreede 2003a; Vreede and Briggs 2005). These characteristic patterns emerge over time as design-team moves from an initial problem statement to a final design concept, requiring consensus. We observe these emergent patterns of characteristic behaviors in the C^2D model as design-teams evolve toward a solution. For a design-team, the management goals and strategies employed should carefully mirror the evolution of a design-team as it progresses across the design landscape. We map these emergent team characteristics to the discrete phases from Figure 2.3 as follows:

- Task Clarification and Analysis of the Problem → Collaboration Diverges
    - The design-team moves from its initial position on the design landscape, corresponding to an initial design conceptual neighborhood, to multiple locations on the design landscape in order to explore feasible design concepts. In the C^2D model, the design-team starts from scratch at a single location, *i.e.* from an assigned location on the landscape. The initial placement of design-teams on the design-landscape in the C^2D model can occur either through an assigned starting location, resulting in a relatively closely clustered initial design-team, as in the default case

or through the random placement of all designers from the design-team on the design-landscape. Typically, design-teams begin from a relatively uniform position, based on their shared analysis of a problem, resulting in a shared understanding of the problem statement prior to its divergent design ideation and concept generation activities.

- Conceptual Generation and Exploration of the Landscape → Collaborations Converges
  - As the design-team develops its understanding of the feasibility of design concepts and as it matures its design preferences, the design-team moves from having many early concepts towards a few concepts with the greatest fitness. In essence, the design-team quickly ferrets out the design concepts with the greatest merit for further study. This aligns to the concept of selecting schemes in the design process. Ideally, these design schemes correspond to design concepts with sufficient fitness, revealed after further exploration, to meet the performance objectives of the design.
- Embodiment of Schemas → Collaboration Organizes
  - As the design-team builds its understanding of the relationships between and within the design concepts, the design-team begins to refine its picture of the relative value of a design concept. This process entails establishing the initial realistic mapping of design parameters to functional requirements.
- Detailed Design and Analysis Focus → Design-team Carefully Evaluates
  - The design further refines its understanding of the relative value of a design concept; this stage firmly establishes the competing design approaches. Designs concepts viewed as inferior to the collaboration quickly fall away, leaving well-entrenched camps of design collaborators.
- Communicate the Design and Solicit Feedback → Design-team Builds Consensus
  - This stage reflects the gradual removal of, in the ideal case, underperforming design concepts through the discussed process of natural selection. Sometimes this results in a protracted period of aligning individual design-team member goals with those of the design collaboration as a whole. Although this process occurs throughout the design process, it becomes most prominent in the final negotiation of a design concept between designers in the collaboration.

As seen in the consensus period, negotiation between multiple designers can often leave the design process protracted; this protraction also commonly results in minimal gains to performance gains as seen in the C^2D model. As a result, we implement the management pressure λ_u parameter provided in equation (3.14) to create an *end-protracted consensus* strategy. This implementation of this strategy depends on a central question; do any of the current design concepts meet the design objectives from a performance perspective? If so, then the management teams and technical leadership teams of the organization step in to help facilitate agreement and consensus more quickly by helping to eliminate underperforming design approaches and concepts. By gradual raising, at each tick while the previous condition holds, the management pressure we in effect ramp up the selectivity from the natural selection dynamic seen previously. We test the strategy of being increasingly selective in the further consideration of design concepts in Hypothesis 11 as discussed in Chapter 1, Section 1.2.

3.3.2 Mechanics of Design-team Formation

The mechanics driving the design-team formation in the C^2D model follow from the procedures outlined by Guimerà et al. (2005) and Wilensky (2007) for the formation of collaborative teams. The formation of the design-team follows from the initial creation of a team and its linkages, and proceeds to a repeated procedure for establishing new-teams and its links. During this process, many of the design-team members must also follow other mechanics to ensure that they leave the collaboration when appropriate and to ensure that the design-team mechanic ceases when the design-team meets the specified stopping criteria for the simulation.

3.3.2.1 Forming the Initial Design-Team

We seed the initial design-team by hatching a team of n newcomers on the design landscape and we color their links. The initial team represents a team of all newcomer-newcomer relationships so we color the links appropriately, according to the convention discussed in Section 3.3.1. In this case, as each link represents newcomer-newcomer relationships we color each link blue. This process represents the first two steps of the design-team formation procedure. We highlight these steps in Figure 3.15 by providing an example case with $n = 3$ newcomers. After starting the procedure and creating this first linked team, we proceed on to the next phase of the process, which involves establishing a new team.

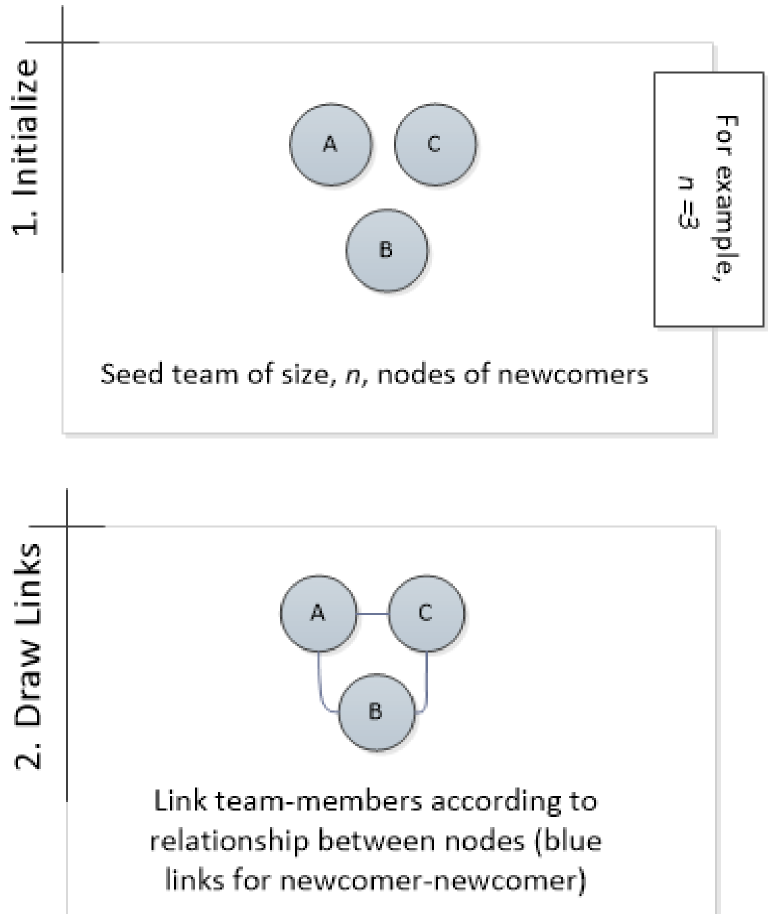


Figure 3.19 Forming the Initial Seed Team in the Design-Team Formation Procedure

3.3.2.2 Establishing and Linking New Teams

At each tick, the procedure establishes a new team with various levels of experience depending on the design-team formation parameterizations, as discussed in Sections 3.3.1.1-3.3.1.3. The parameters includes the probability of a design-team incorporating a newcomer p and the probability of repeating a collaboration q. As these relationships and design-teams develop, these procedures continually redraw links as shown in Step 2 above.

3.3.2.2.1 Selecting Newcomers

The probability of selecting a design-team follows from the parameter p as implemented in the model. We begin the procedure of establishing a new team by selecting a design collaborator at random and drawing a random number between zero and one. We compare that value to p, if the random value remains less than or equal to the set value for the parameter p a newcomer joins the collaboration. In other words, if the value drawn were 0.75 and the probability of accepting a newcomer remains at or above 75%, a newcomer would form. We continue this procedure until the team-size reaches the desired n. However, if at any time during the procedure the draw results in a value that exceeds the parameter p the designer must then move to select an incumbent based on the appropriate procedure.

3.3.2.2.2 Selecting Incumbents

The probability of selecting an incumbent of an existing design-team member follows from the parameter q as implemented in the model. We perform this operation each time the design-team selects an incumbent, which occurs with probability $1 - p$. We begin by generating a random number for the currently selected design-team member. We compare the drawn value to the parameter q. If the random value remains less than or equal to the q value, the design-team repeats a current collaboration of the design-team.

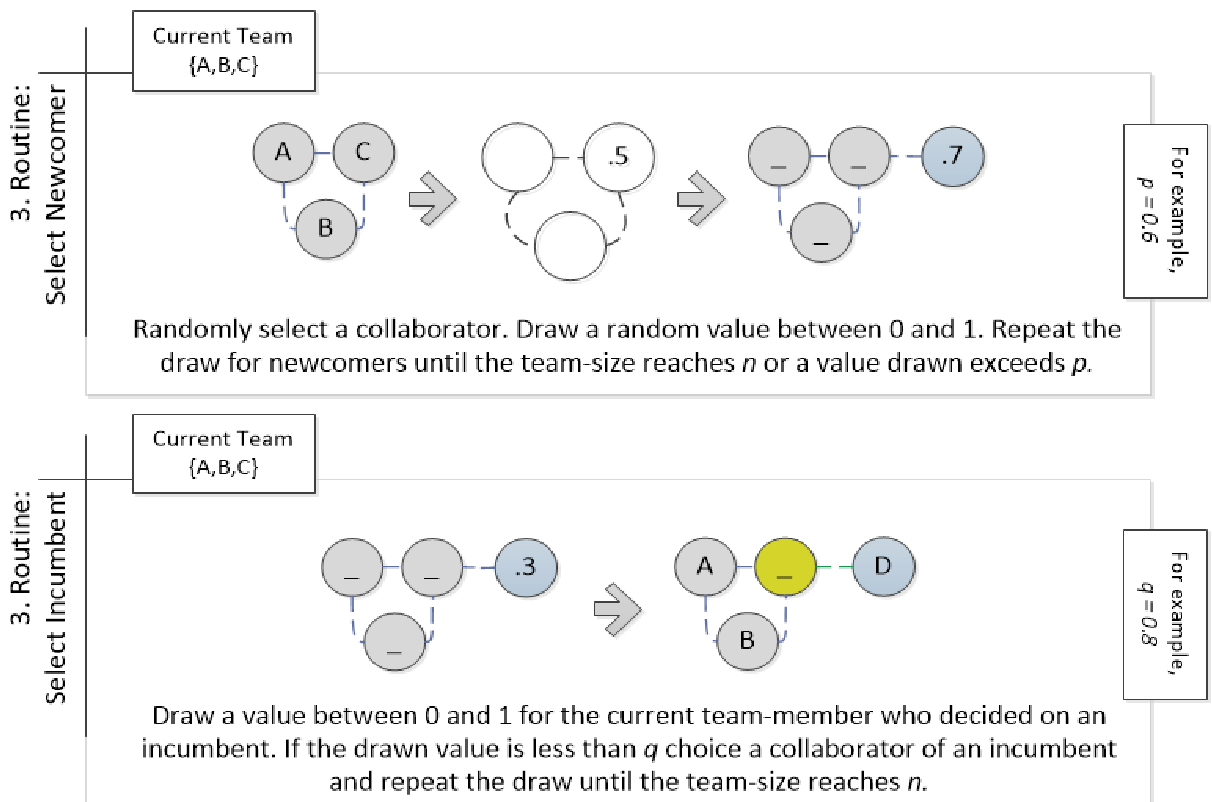


Figure 3.20 Design-Team Formation Routine. The procedure begins by randomly selecting a designer, in this example designer C. After having selected this designer, a value between zero and one determines if the design-team incorporates a newcomer or moves onto an incumbent. The design-team includes a collaborator of a current design-team member, *i.e.* a currently linked member of the collaboration, if available. Otherwise, the design-team selects a collaborator at random.

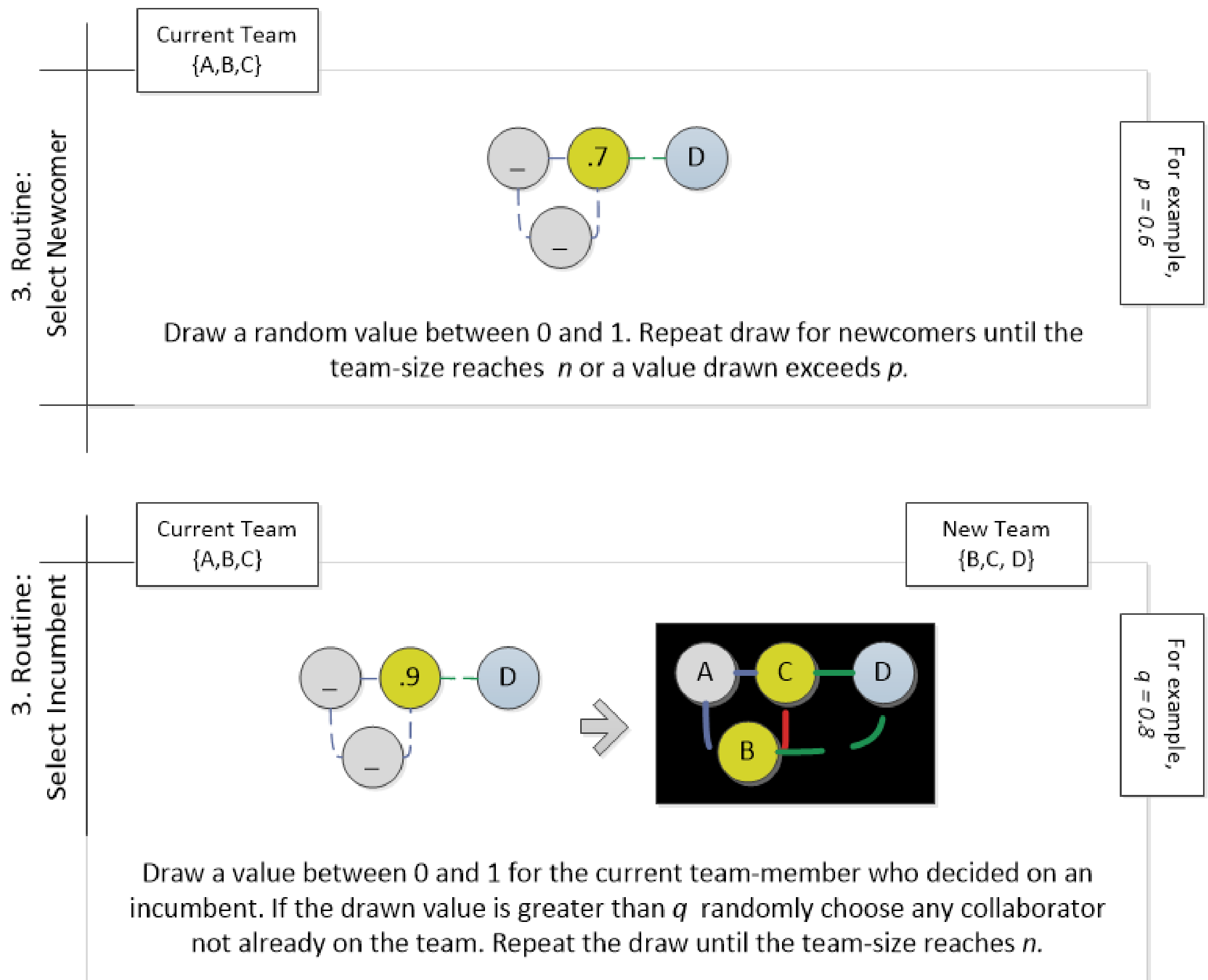


Figure 3.21 Design-Team Formation Cycle. After the design-team selects an incumbent, the design-team formation routine returns to the newcomer selection process. In this instance, the value drawn during the newcomer selection procedure exceeds the value for the newcomer parameter p and results in the final design-team member arising from the incumbent selection process. We underline design-team members under consideration in a procedure, in the case all of the possible incumbents. In this final incumbent selection process, the value drawn exceeds the value for q, resulting in the random selection of designer B from the overall collaboration. With each team-member selection, we update its links. We draw the design-team links according to their relationship as described by Wilensky (2007). This includes coloring newcomer-newcomer links blue, incumbent-incumbent links yellow, newcomer-incumbent links green, and repeated collaborations between the same designers red. Each new team ensures through this procedure that all design-team members of the new team share a link to one another. The final team selection in the example includes designers B, C, and D. In the above example, the red link between designers B and C represents a repeated collaboration. Similarly, the green links between the designers C and D, and between B and D represent a link between a newcomer and an incumbent. In this example the key team formation parameter took on values according to $n = 3$, $q = 0.8$, and $p = 0.6$.

3.3.2.3 Leaving the Design-Team

As previously discussed in Section 3.3.1.5 and 3.3.1.6 design-team members occasionally depart from the overall design collaboration. We view these departing team-members as unproductive as either they have stopped contributing to the collaboration or their design concepts no longer align to higher performing design alternatives. We explore these relationships more formally in equations (3.13) and (3.14).

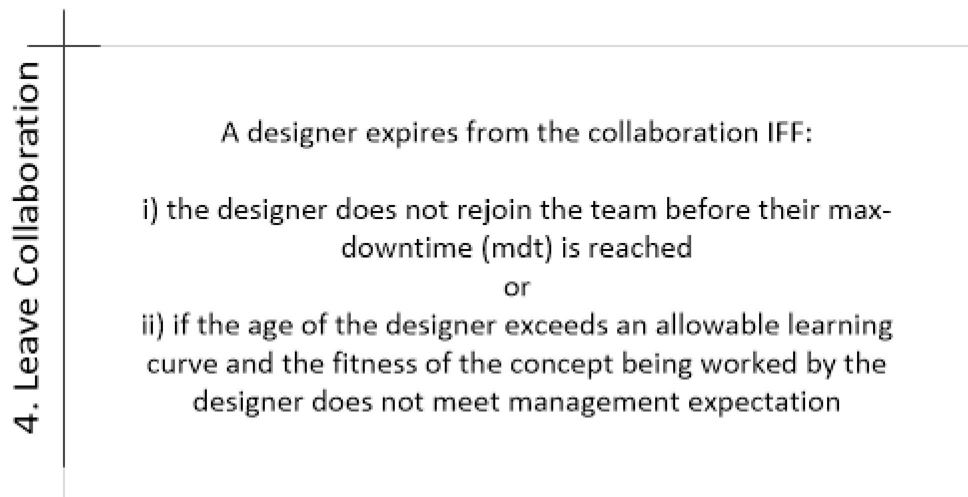


Figure 3.22 Leaving the Collaboration. The design-team formation procedure in the C²D model also encompasses the pathway for unproductive design-team members to leave the collaboration.

3.3.2.4 Repetition and Stopping Criteria

This team-formation process occurs continually in the C^2D until the design-team reaches some predefined stopping condition. The default stopping condition for the C^2D model is that the current average fitness of the design-team exceeds the objective fitness.

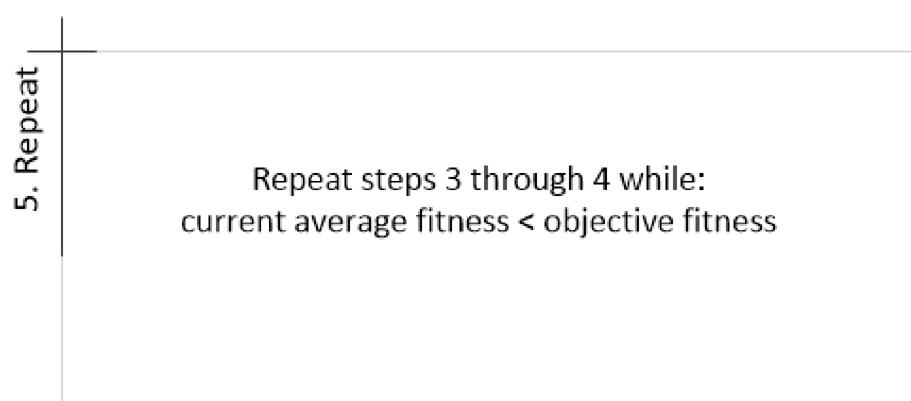


Figure 3.23 Generic Repetition of the Design-Team Formation Process. The final stopping conditions vary based on the selections of decision criteria used by the C²D modelling analyst.

3.3.2.5 Example of Design-team Formations

The construction of these design-teams, as shown in the procedure, follow from the selection of design-team formation parameters. Figure 3.24 provides an overview of the role of these design parameters in the evolution of team-structures over time.

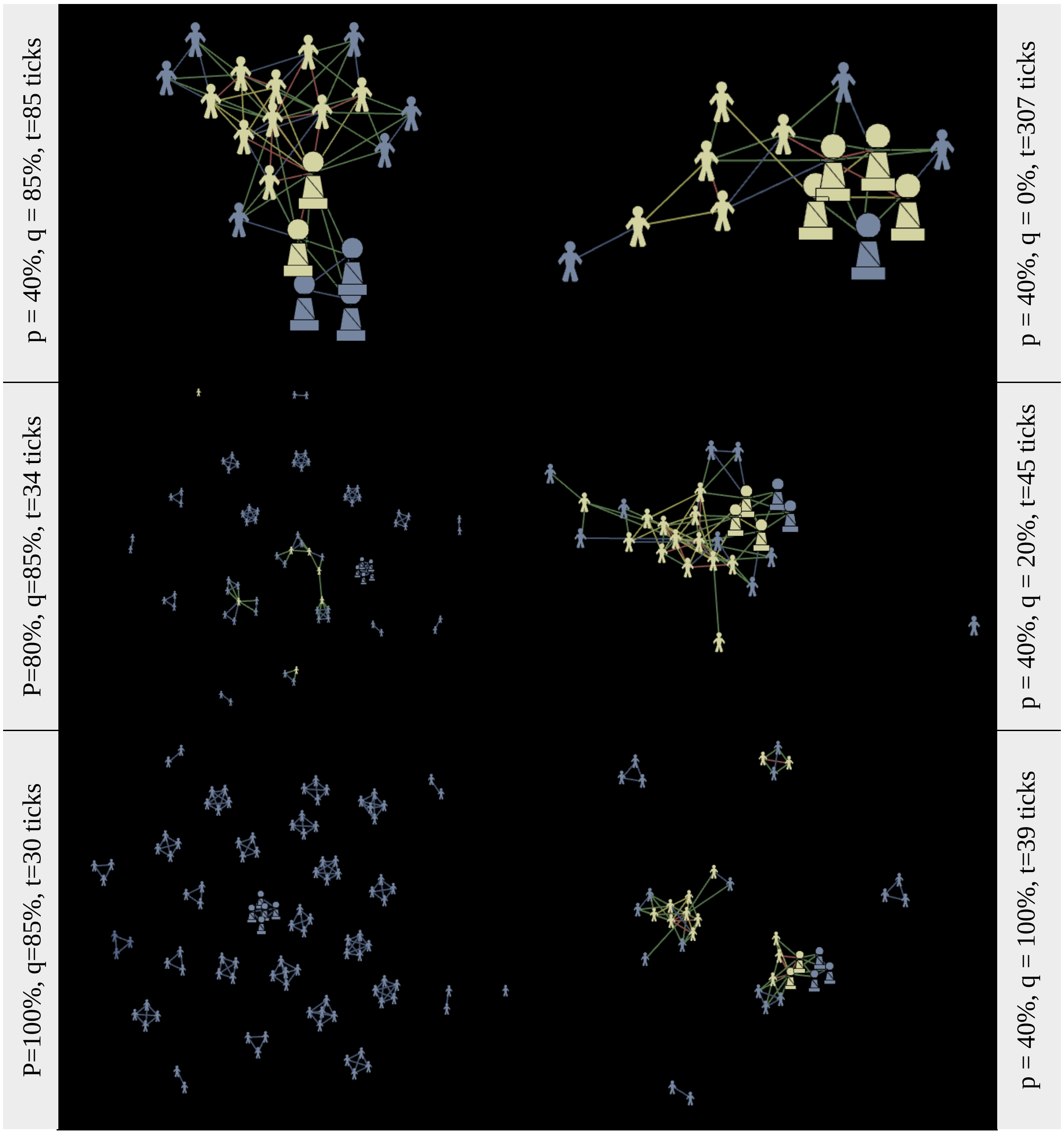


Figure 3.24 Visualizations of the Network Structure for a Team Size $n = 5$ with Various Team-Formation Parameters. These structures represent the local network structures present after the design collaboration reaches consensus and the C²D model (v3.4.2) terminates at time t. We use the same seed (4093), smoothness (72%), mdt (40 ticks), goal-fitness (78); we also use the same strategies, including dynamically cycling mutation. We only vary the specified p and q parameters.

The C[2]D model represents the designers as agents exploring the design-landscape through an agent-based modelling environment. These designer agents follow strategies to act on their fitness goals. In the context of Data Envelopment Analysis (DEA), we establish these designer agents as the decision-making units (DMUs) responsible for executing the design process and the search of the design-landscape. We assume that these agent-based DMUS (ADMUs), for purposes of this research, adequately represent the relevant characteristics and behaviors of individual components of the Designer-Artifact-User (DAU) complex adaptive system (CAS). In so doing, we build upon the conceptual relationships established by Dougherty, Ambler, and Triantis (2014) relating ADMUs to more general management systems in the Complex Adaptive Productive Efficiency Method (CAPEM) framework. Intuitively, we understand that for an ADMU to make a decision it must have a goal and either implicit or explicit rules that guide these decisions. We represent the goal-attainment model for ADMUs in the C[2]D model as an analogy to the engineering design process itself, as discussed in Chapter 2, Figure 2.3. These goals represent collective goals (cf. Section 3.3.4) to find effective design solutions (i.e. sufficient fitness) efficiently (e.g. with a minimum required design time). These collective goals naturally lend themselves to the DEA construct of an optimization model, with its objectives and constraints. For example, we can tailor equation 2.16 to provide an objective function for fitness in equation 3.15 below.

$$F(x) = \frac{1}{f}\sum_{j=1}^{f} f_j(x_{i_1(j)}, x_{i_2(j)}, \dots, x_{i_{p_j}})$$

Where:

p_j the number of FRs affecting a design parameter DP_j (3.15)

$i = 1 \dots N$ the FRs affecting a design parameter i

$j = 1 \dots f$ the DPs controlled by each functional requirement j

$\left\{i_1(j), i_2(j), \dots, i_{p_j}\right\} \subset \{1, \dots, N\}$

In other words, the DAU works to achieve fitness collectively by maximizing the fitness function $F(x)$ where the fitness contribution f_j of the design parameter j depends on the resulting fitness to requirements i and Kother requirements. The f parameter defines the number of design parameters each design shall have, while K defines the degree of inter-dependence within the design. In the C^{2}D approach, as discussed earlier in Section 3.2.3, we can randomly generate these fitness landscapes assuming maximal indifference (when the relationships between parameters and requirements are not known) using the function $F_i: \{0,1\}^{K+1} \rightarrow R$, which assigns a value from the uniform distribution in the range $(0,1)$ to each of its 2^{K+1} inputs, from equation (3.6). The values for $j_1 \dots j_K$ are chosen randomly from $1 \dots N$ (random) or from the left and right of functional requirement i (nearest neighbor). The "ruggedness" of the resulting fitness landscape remains tunable by changing the value of K and thus the number of interacting design parameters per functional requirement. Low values of K indicate few interactions and high values of K indicate high degrees of complexity in a design.

As part of the C^{2}D implementation in this dissertation, we assume that each designer operates with respect to a shared understanding of the fitness F_i. However, we include the possibility of heterogeneous preferences as an area for future research. For example, members of the DAU more accurately represents various communities with their own design preferences. As part of our recommendations for continued research, we propose representing these differences through coevolving fitness functions for the individual design communities. As a result, the adaptive movements of one design community can influence and drastically change the fitness landscape for another design constituency at each increment of time. For example, increases in the thermal budget on a design for a spacecraft can drastically improve or limit the available options for a battery or propulsion subsystem designer. We can theoretically account for these differences through the incorporation of a coevolution dynamic. One approach would include the introduction of a weight to each fitness contribution for every DAU constituency given by s. In summary, we can expand the C^{2}D approach similar to Vidgen and Padget (2009) to introduce the total number of competing (i.e. interacting) design preference communities in the DAU *(S*), the number of design communities $(s \in S)$ that are interdependent (X), and the number of functional requirements (C) from one design community within S that influences another design community similarly with S. This weight equation for our binary case follows in equation 3.16 after Blonder (2007).

$$W_{FR,s} = 2^{1+X_{FR,s}+C_{FR,s}} \quad (3.16)$$

However, within the current research, obtaining collective goals requires the coordinated actions of the individual designers, each with their own goals, rules, and percepts for decision-making. We represent the process of obtaining design objectives through the natural system metaphor of obtaining fitness, *i.e.* individual designers act on their own internal goals to maximize their own performance subject to its own rules and percepts. However, unlike the coevolution possibility summarized above, each individual designer maintains a common understanding of the design objective, *i.e.* each designer shares a common fitness model and design landscape. Representing individual DAU decision-makers as individual ADMUs on this common landscape provides the opportunity to incorporate a very large number of similar decision-makers and multiple uniquely different decision-making units each with their own goals, rules, perceptions and actions (Miller and Page 2002). As semi-open entities, each of the ADMUs meet the DEA and decision-making theory requirement for independence among DMUs as a single designer pursues its own internal goals and adheres only to its own internal rules. Although in the C^2D approach, it does so in a common environment (i.e. common objective function). These ADMUs accept selected pieces of information, like the current state of other designers through its communications and linkages to the larger collective. The designer ADMU remains both semi-open and autonomous. In other words, its behaviors result only from its own choices about how to react and behave, based on its own goals and rules, and based on the information it receives (Holland 1998).[35]

Although we limit our approach to the individual designer and the overall designer collaboration, consistent with the principles of CAS thinking, we can define the ADMU at various levels of granularity as long as those levels of granularity remain tractable. For example, future C^2D research could define each ADMU as a complex of design-teams working on a subsystem, where multiple subsystem design-teams coevolve with one another and the larger supremal design

[35] As in any socio-system, these individual and independent goals introduce the possibility of agency costs to the collaboration as the designers can often have divergent interests form the overall goals of the collective, *i.e.* the collaboration. For example, at times, the individual maximization of fitness for an individual designer in the C^2D model can limit the performance of the collective by protracting the time required for goal attainment and it can even in some cases reduce the resulting final fitness for a design collaboration. In future models, the incorporation of coevolution can strengthen this representation by allowing for varying preference models. The current model enforce a uniform representation of the landscape and objective function for all designers (cf. equation 3.15).

collaboration to obtain design solutions, *i.e.* fitness. The similarity and analogy between the human-like ABM agent with its goals, rules, percepts, actions and the analogous characteristics of a DAU decision-maker (i.e. the designer) underpins this analysis. The CAS ABM computing language semantics and syntax when combined with the concepts of DEA and its formulations (cf. Chapter 2, Section 2.5) provides a clear, concise, yet rich means for expressing these goals, rules, and precepts of the model (Dougherty 2014). We uses these semantics and syntax in Chapter 4 to represent concisely the goals, rules, and construction of the model discussed below in terms of constraint generating procedures.

3.3.3.1 Individual Goals

An individual decision-maker within a larger DAU system may have, in general, a wide range of desired outcomes or goals. The primary goal of any designer centers on its continuous improvement of performance, through the maximization of its fitness and its ability to grow the collaboration. In other words, a C^2D designer has the goal of finding a design solution that meets or exceeds the design objective and passing that solution onward to future generations. The fitness it can achieve, however, remains limited to accessible fitness locations on the design landscape enabled by its location within the collaborative design network. We represent this concept of fitness through the construction of the design landscape. We can similarly describe the fitness characteristics of the design landscape through a function, similar to any production or value function. The CAS ABM objective function, the DEA production function, and the Collopy and Hollingsworth (2011) value function for engineering each similarly provide the equivalent of a goal. In a DEA production function, a common goal includes finding the optimum possible production for a given set of inputs (Cooper, Seiford, and Tone 2007). Similarly, the Collopy and Hollingsworth (2011) value function describes the optimum value for a design for a given set of design inputs. The fitness of the design landscape in C^2D similarly arises from a set of inputs (i.e. given functional requirements and possible design parameters). However, the C^2D design landscape does not necessarily follow a parametric closed form value function, as evidenced by the ruggedness of its design landscape. Nevertheless, each C^2D ADMU seeks the same continuous improvement goal and, although not always possible due to the ruggedness of the landscape, each designer attempts to find maximal fitness.[36]

3.3.3.2 Individual Rules

Decision-makers in any general management system employ a set of common business rules (Jeston and Nelis 2014). Business rules embody the collective intelligence and wisdom of the business area or domain. The constraints of any optimization model similarly represent the concept of well-formed business rules. However, adherence to these rules by the individual designers follows strictly from the discipline of the designers themselves, *i.e.* their own internal adoption of the rules. For example, designers must remain aligned to the goals of the collaboration. More concretely, these business rules, or in the C^2D context the design rules, provide the basis for individual designers to locate design solutions. These individual decision-makers follow the rational decision making process for design when performing the hill-climbing procedure, *i.e.* designers compare their fitness to the accessible neighboring design solution concepts. This process remains identical to the accepted and commonly employed utility-based rational decision-making models for design (Hazelrigg 1998).

Although the collaboration can incorporate radical innovation through the incorporation of a newcomer, individual designers can only remain in their current location (depending on the design strategy) or move to an increasingly fitter neighboring design location at each increment of time. By default, we implement the search rule for the individual designers through both the hill climbing and natural selection analogies. In the hill climbing case, if any neighboring locations for an ADMU has improved fitness, then the ADMU moves to that improved location on the design landscape. The natural selection dynamic ensures that the individual designers compare with greater fitness are more likely to contribute to a design team and to grow the collaboration. Because of this rule construct, individual designers often anchor themselves to local peak fitness locations.

[36] In order to remain fully consistent with convexity constraints common in most productive efficiency and value approaches, one can envision the design landscape as a function of convex functions. In this construct, the individual designers remain confined to their local neighborhoods, which we define through convexity. In other words, designers in the collaboration form subsets of designers (e.g. design factions) based on their achievable optima. In effect, as designers explore the design landscape they can split (cf. allopatric speciation) into several solutions. This speciation remains especially prevalent when adopting the strategy of hill climbing in the C^2D model. Additionally we allow parametric fitness functions to form the landscape and enforce convexity. Nevertheless, we relax the requirement for convexity in general can be viewed as overly restrictive (Cherchye, Laurens, Kuosmanen, and Post 2000). As a result, we relax this axiom of convex production in our C^2D general simulations.

Once there, these designers advocate for the particular merits of the corresponding design solution they occupy. As the design process continues, eventually either the collaboration coalesces around these positions or the designers at these locations decide to leave the collaboration during the consensus and design rework processes. The consensus and design rework processes reconcile the relative fitness values of the discovered locations from the design collaboration. In part, this process comes to conclusion when the collaboration adjudicates all competing design solutions, *i.e.* dislodging designers from all competing design approaches. However, from the perspective of the individual designer, the central rule for searching the design landscape remains simple, to seek out and attain the best accessible fitness. However, other search strategies, discussed as part of Section 3.3.5, can augment the baseline rules governing search and provide improved search characteristics that help overcome these limitations.

Additionally, individual designers must also decide with whom to collaborate if selected to participate in the design-team based on the team-formation mechanisms discussed in Section 3.3.2. A randomly selected designer must decide either to bring in a newcomer or incumbent, including what type of incumbent if applicable. The associated design-team formation parameters inform the likelihoods of these occurrences. We assume that we can adequately represent the aggregate team-formation rules for a design effort using three basic team-parameters, to include the likelihood to incorporate a newcomer, the likelihood to repeat a collaboration, and team-size. Moreover, the designer must decide what degree of diversity of thought or expertise any newcomer possesses, subject to the maximum diversity constraint imposed by the larger DAU management system.

Furthermore, members of the collaboration must also adhere to certain rules with regard to their continued participation in the design effort. Chiefly, collaborators must remain minimally fit and minimally active; otherwise, they must leave the collaboration. If an individual collaborator remains underutilized for too long it leaves the collaboration following the rule highlighted by equation (3.13). Similarly, if the collaborator remains anchored in a relatively unfit position or on an insufficiently fit design solution, it also leaves the collaboration according to equation (3.14).

We implement these rules explicitly into the C^2D model using NetLogo; these rules provide the mechanisms for the constraint-generating procedures highlighted in Chapter 4. It is through the individual decision-making of designers, especially with regard to team formation and collaboration divestment, that gives rise to the characteristics of design performance. We assume, for purposes of the C^2D model, that these parameters adequately capture the relevant characteristics to relate the designer, the design-teams, the resulting design collaboration, and the design performance characteristics involving their search of complex design spaces.

3.3.3.3 Individual Percepts

An individual component decision-maker within a larger DAU management system may have a wide range of factors that it can sense or perceive. Individual decision-makers, for example, often have a massive array of available information, even though they only have the ability to understand and actually utilize a small sub-set of this information. This information includes the state of design-trade allocations, such as the allocations of thermal, power, or geometric design budgets. In traditional DEA analysis, a DMU has information only about its own factors of production (Cooper, Seiford, and Tone 2007). Dougherty, Ambler, and Triantis (2014) expanded beyond this limitation by enabling the direct sharing of information between DMUS in the CAPEM model using the CAS ABM equivalent of ADMUs. In the C^2D model, information exchanges similarly occur between ADMUs. Designers share information via their linkages to the collaboration. This information includes the relative fitness of the connected designers. Collaborators can then perceive the approximate fitness of the overall collaboration through the DAU management system environment. Each design strategy relies on access to this perceived information as it drives the actions via the highlighted rules (i.e. mechanisms) above.

Examples of the percepts available to each designer in the C^2D model include:

- An understanding of the level of experience of itself and other designers (i.e. incumbency);
- The nature of relationships between designers (e.g. new-collaboration between an incumbent and a newcomer);
- Which designers in the collaboration currently constitute the newly formed design-team;
- Its own current downtime (i.e. ticks since last on the design-team);
- Its own age (i.e. number of ticks since joining the design-team);
- The optimality of itself and others (i.e. does its location on the design landscape coincides with an optimum?);
- The fitness of itself and others on the design landscape; and,
- The minimum threshold fitness level (i.e. minimum satisficing design fitness).

3.3.3.4 Individual Actions

Actions taken by one ADMU may or may not affect the ability of another ADMU to achieve a desired position on the design landscape. With each design-team formation, the overall design network responsible for enabling and supporting the design collaboration morphs. With this change, the achievability of certain optima ebb and flow with the dynamism of the collaboration network and its support. In the traditional DEA approach, the actions of DMUs remain independent. However, in the C^2D model, a designer ADMU reports its current position on the design landscape, as well as its information about its location (e.g. fitness, optimality), to the ABM environment. Other designers may or may not choose to perceive and act on this information based on the design strategies employed. Generally, in C^2D all designers not currently at an optimum perceive the state of optimality and fitness for all ADMUs in each increment of time. Ultimately, action in most C^2D design strategies arise from the nature of the teams formed as well as the degree of diversity or lack thereof among newcomers to the collaboration. The exchange of information between collaborators provides insights necessary for individual designers to execute on the design team-formation strategies, highlighted in Section 3.3.5, such as varying the diversity of the team. For example, one design strategy eliminates diversity from future newcomers when a current collaborator finds a peak design location (i.e. a local or global optimum) with sufficient fitness to meet design objectives.

The actions available to the designer, based on its percepts and design strategy, when searching the design landscape include:

- Move to a neighboring design location with increased fitness; or,
- Remain at its current location, providing a jumping-off location for a future newcomer.
  - Design strategies discussed in Section 3.3.5 provide the rules for these actions. We examine possible generic strategies and their variants; exploring alternative design strategies and their linkages to other well known, as discussed by Cormen, Lierson, and Rivest (1990), heuristics and studied algorithms (e.g. best-first search, epsilon-greedy algorithm, simulated annealing metaheuristic) remain areas for ongoing research.

Additionally, select design-team members decide:

- Whether to include a newcomer or include an incumbent, including what type of each;

- Whether to repeat a collaboration of an existing team-member; and
- Whether to leave the collaboration.

Designers commonly implement these policies through a shared set of design rules; sometimes these individual designers align to the collective goals of the collaboration when advantageous to achieving their own individual goals of optimizing performance. However, the available actions made available to these individuals can often remain constrained by their environment and the collective rules governing design. In the C^2D implementation, each designer adapts to the landscape relative to its own fitness.

3.3.4 Collective Influences in Decision-Making

Gaining insights into the choices of individual decision-makers over time can only be of value when understood in the context of the collective complex adaptive behaviors exhibited by the system as a whole (Holland 1999). Gaining insights into this collective and emergent behavior of the system is as important, potentially even more important, to some decision-makers, than the choices made by individual decision-makers, as in the case when constructing a DAU-level total productivity factor for possible comparisons between different DAUs (Craig and Harris 1973). It is through these relationships with respect to the greater collective collaboration that the overall C^2D model and its purpose comes into focus. We examine ways to promote and control an environment of collaboration, as opposed to simply imposing rules on the individual designers search behaviors.

3.3.4.1 Collective Goals

Consistent with DEA methods, the DAU management system seeks as a collective to maximize or minimize an objective through the distributed local optimizations of the individual designers. In our case, the DAU system seeks to minimize the time required for finding an agreed to design solution while imposing the constraint of a minimally sufficient fitness value. In our case, these fitness objectives may not necessarily correspond to a global maximum, but rather they may correspond to a “good enough” solution for an organization. This typically, in the case of new product development, includes introducing new incremental functionality to the marketplace to preserve time to market. However, the new functionality may not represent the best possible combination of technology components in favor instead of getting some acceptable level of functionality to the market. For example, although the global maximum of a design landscape in

C^2D represents a fitness score of 100%, whereas we commonly set the goal for the DAU to some lesser level of fitness (e.g. 92%).[37]

3.3.4.2 Collective Rules

Consistent with the theory of the firm, the C^2D approach to performance, in part, follows from a relaxed set of axioms governing the general relationships for any production system (Cooper, Seiford and Tone 2007). From a CAS ABM perspective, these axioms help constitute collective system rules, which both enable and constrain the system as a whole. These rules help to ensure consistency of the design landscape to fundamental theories of production, which enable the analogy of the DAU system to a production system in the context of DEA as previously described in Chapter 2, Section 2.5.1.1.

However, in addition to the construction of the modelling environment, collective rules also govern the behaviors of the designers through the concept of stopping criteria. The general C^2D model not only enforces the requirement for a minimum fitness level, it also requires agreement from all of its individual design members on a design concept, *i.e.* consensus. The collective collaboration may also provide additional rules, depending on adopted design and management strategies, to enforce reasonable timeliness in the negotiation process between collaboration members. For example, the collective rules governing the collaboration may dynamically set the management pressure to drive a design solution to fruition (*i.e.* a scale for the natural selection dynamic).

3.3.4.3 Collective Percepts and Actions

Within the scope of this research, there are no collective percepts or actions external to the DAU modelling environment, *i.e.* C^2D remains a closed system. Real world DAU systems may collectively perceive aspects of their larger environment and generally accept exogenous inputs as if they were an open system. Similarly, real world DAU systems generate engineered-systems that act on their environment by improving the technology possibilities for future designs, but this exploratory research focuses exclusively on collective behaviors driven solely by the decisions of

[37] The C^2D model allows the analyst to test for the effects of goal setting on performance. In many cases setting a goal equal to the global maxima, although it may eventually lead to the highest possible fitness of 100, extends the time to market for a design beyond any reasonable limit for a competitive firm. Often, we can obtain the same global maxima by slightly relaxing the fitness objective. For example, in the C^2D model (v3.4) we can achieve the global maxima in 274 ticks as opposed to 450 ticks by relaxing the fitness goal objective from 100% to 99.5%, with all else being equal. In this sample run, we use the same parameters $n = 5,\ p = 45\%,\ q = 85\%, mdt = 40\ ticks, S = 72\%$, and a constant $Seed = 2436$. We also use the same defaulted strategy settings discussed in Section 3.3.5.

individual designers. Analysis of the environment beyond the DAU system itself requires hierarchical aggregation and a change in the granularity of the analysis (Holland 1999). To perform this kind of analysis would require treating the collective DAU system as a single agent or an autonomous cluster of agents, in a larger CAS ABM environment. The value and means of doing so remain beyond the scope of this research. However, the approach potentially offers an alternative view of the scaling issue, i.e., going from individual designers to groups of designers working at the subsystem or system level.

3.3.4.4 Collective Interactions, Feedback, and Emergence

The interactions between the individual designers and the DAU environment follows from collective system factors such as standing corporate policies and rules, as well as an understanding of the availability of resources to support the exploration or exploitation of a design concept. From the CAS ABM environment, an agent senses global variables such as the physical limits of the environment, *i.e.* distance measures on the design landscape and search times. Distance in this case translates into a conceptual measure relating design approaches and differences in the corresponding relationships between design parameters and functional requirements.

In the presented CAS ABM analysis, feedback represents an awareness of changes in the states of other agents and the elements of the CAS ABM environment (Holland 1999). Such a representation provides a means of defining feedback at a very granular level. In the context of design, individual design collaborators sense and acquire as much or as little information as desired or allowed by its neighboring designer, we assume that each collaborative agent freely choices to collaborate. These designers each adhere to their own rules for sensing, responding to, and sharing information. Each designer also receives feedback from the larger collaboration and the CAS ABM environment. Individual designers also influence other designers through their impacts on the collaboration and its growth. These interactions and continuous feedback processes in design provides the source of the collective behaviors demonstrated by the design collaborations. These behaviors give rise to the emergent behaviors in a design collaboration. Implemented appropriately, analyst may investigate the behaviors that are directly traceable to individual goals and rules and match them to beneficial patterns of overall collective behavior. Ideally, harnessing complexity to incentive beneficial emergent and natural behaviors that lead to improved design outcomes, *e.g.* increased artefact fitness and decreased time to market.

3.3.4.5 AGENT GOALS, VALUE PROCESS, AND THE DESIGN LANDSCAPE

The goal of any DAU management system with respect to performance revolves around the constant improvement of design fitness; in particular, this involves improving fitness (output-maximization) or minimizing to the greatest possible degree, the inputs, including time, required for producing a given level of fitness (input-minimization). The fundamental challenges for any management system rests on its ability to know what is possible given the underlying technology (Gilbert, 2008). This notion remains doubly true with regards to design; we describe this art of the possible for design through the concept the design landscape and its representation of feasibility. Understanding of the design landscape similarly occurs through the communication and linkages between individual designers.

In DEA, the benchmark of what is possible follows from the specification of the mapping between the inputs and the outputs (production process representation of the technology) and the position of the frontier. DEA DMUs know what is possible by checking with all other similar DMUs and determining which ones are most efficient. The subset of DMUs that either maximize outputs or minimize inputs relative to the other DMU in the set, provide performance benchmarks. When the productive efficiencies of all DMUs (in terms of inputs, outputs or ratios) are normalized and plotted on a coordinate scale the most efficient DMUs form a piecewise linear curve called the efficient frontier. The efficient frontier is the benchmark or goal that all other DMU seek to achieve. Inefficient agent DMUs make modifications, in whatever ways are available to them, to become as efficient as those on the efficient frontier, the benchmark of efficiency. Reaching the efficient frontier is the goal of each agent DMU in DEA. Driven by polices of the DAU collaboration and based on the rules of team-formation, designer ADMUs similarly seeks to minimize the design search time for individual designers, while also meeting an agreed to minimum fitness objective, for attaining feasible design solutions represented by the design landscape. The design landscape provides the efficient frontier equivalent in C^2D as it represents the theoretical or efficient relationships between design parameters and functional requirements. As such, we assume all ADMUs in the DAU only explore efficient specifications between functional requirements and design parameters. Therefore, we view efficiency in the C^2D as a matter of time spent exploring the design landscape and effectiveness as a matter of meeting fitness levels. In other words, C^2D views effectiveness as a measure of finding sufficiently fit design solutions, whereas we view efficiency as achieving design goals quickly.

3.3.5 Collaborative Design Strategies

As we have seen, design remains a complex, adaptive system comprising many physical, cognitive, and socio-technical based interactions. Design strategies enable the designer-artifact-user (DAU) system to evolve successfully to meet the challenges presented from a given design landscape and its complexity. We define collaborative design strategies in particular as the use of a method to ensure the formation, development, and sustainment of a robust collaborative network of designers. These resulting collaborations remain capable in exploiting their current distinctive capabilities (its fitness function) on or near its current fitness peaks and equally capable of exploring the strategic design landscape. These strategies enable design collaborations to both explore their technical ecosystem for design improvements and identify future design opportunities beyond the scope of current design activities. Successful design strategies are those that positively influence the evolution of a design in favor of the organization benefiting for the enactment or development of the strategy, in our case in favor of the overall collective design collaboration. These strategies help the design collaboration: define the nature of the design collaboration, understand and continually perceive the design landscape, anticipate the ways the collaboration and its design activities may change, and to influence the way that the collaboration develops and obtains goals. Ultimately, these strategies motivate the beneficial actions and collaborations among the individual designers – propelling a design effort toward successful design outcomes. For C^2D the design collaboration consists of the collective goal to achieve an acceptable agreed to design solution in the minimum search time possible. In order to explore these goals, C^2D model provides a platform for testing strategies. In its general use, the model consists of some core strategic elements, as well as several strategies, discussed below, for exploring the role of diversity and the role of technical management in limiting the time necessary to obtain design solution.

3.3.5.1 Core C^2D Strategy Elements

The goal of any DAU management system with respect to performance revolves around the constant improvement of design fitness; in particular, this involves improving fitness (output-maximization concept) for the individual designers to an acceptable state while minimizing the overall search times required to find these design solutions. In order to achieve these goals, the C^2D model explores several simultaneous underlying dynamics that provide a default metaheuristic, *i.e.* a high-level procedure designed to find, generate, and select a sufficiently fit design solution. These underlying dynamics, as discussed individually, include the dynamics of natural selection, maximum downtime, hill climbing, and coalescence. We can also decide to implement these factors individually or in any combination with one another.

3.3.5.1.1 Natural Selection: Aging of Designers

Although C^2D does not follow traditional utility formulations commonly employed in technical decision-making, it does result from the rules of natural selection where points of improved fitness provide an advantage to fitter designs against competing fit design concepts. More specifically, a comparatively fitter location on the design landscape has the increased likelihood for reproduction and the further adaption of a designer agent-based decision making units (ADMUs). In terms of the design analogy and the natural selection metaphor, these locations of improved fitness have the greatest probability of accessing resources from the DAU design management system, including access to potential new team members. The ability to recruit other design agents to a design collaboration in the C^2D context represents the biological equivalency of fecundity, *i.e.* the ability to reproduce. This natural selection dynamic, as mimicked through our genetic algorithm implementation, utilizes the representation of the design landscape and fitness of the designers on this landscape to inform its operation.

Each member of the design collaboration ages, as discussed in Sections 3.3.1.6 and 3.3.2.3. This aging process provides for the underlying natural selection dynamic underpinning the model and its implementation of the dynamic. Designers at each tick age by a corresponding tick. Individual design collaborators that age beyond their relative contributions, as measured in fitness, leave the collaboration. In other words, if a relatively experienced ADMU designer persists in the pursuit of unfit ideas the DAU may decide to collaborate no longer with that ADMU. However, we ensure that each member of the collaboration receives a minimum time on the collaboration. Conceptually we relate this starting time as a time that corresponds to a necessary and anticipated learning curve of a current designer joining the collaboration. After this learning period or maturation period expires, unfit designers increasingly leave the collaboration, which in turn makes it more likely for fit solutions to compete for resources and recruit new team members. Eventually, unfit collaboration members leave when their current fitness levels fails to exceed a random value between zero and the fitness objective. This random fitness objective corresponds to the notion that coarse graining occurs (the scaling of the natural selection mechanic to match the uncertainty of its measurement) over time in the design process; with more time comes more understanding of the relative merits of a design. This increased understanding results in more opportunities to get rid of underperforming design concepts and to focus on discovered design approaches more likely to succeed.

3.3.5.1.2 Maximum Downtime

Each member of a design collaboration must remain active to some degree in the design effort. If a member of the collaboration continually fails to participate in a design-team, it will leave the collaboration and design effort after it reaches its maximum downtime. This corresponds to the observed behavior of teams and collaborations, where inactive members will seek participation in other activities or projects that favor their participation. This maximum downtime represents a critical component in the balancing the size of a collaboration over time. The use of this dynamic relies on the user-defined maximum downtime.

3.3.5.1.3 Hill Climbing

Each member of the design collaboration works to follow its internal goal of maximizing fitness. As such, each member of the design-team follows the simple hill climbing procedure. At the beginning of each increment of time, each member of the collaboration examines the relative fitness values for its neighboring design concepts. It proceeds by maximizing its fitness by moving to its most fit neighbor. In total, however, the combined efforts of the individual hill climbing efforts for the collaboration as a whole over time similarly resembles a version of the random-restart hill climbing model. For example, the random-restart hill climbing model (also known as the Shotgun hill climbing model) starts each new iteration from a new random initial point on the landscape, climbing the landscape multiple times from multiple locations. In this strategy, the collaboration maintains the best peaks over all of its iterations. As a result, increasingly fit optima gradually emerge through the application of this meta-algorithm. We similarly gain the same effect through the C^2D model. For example, the use of diversity similarly provides a new starting point on the design landscape when searching for fitness.

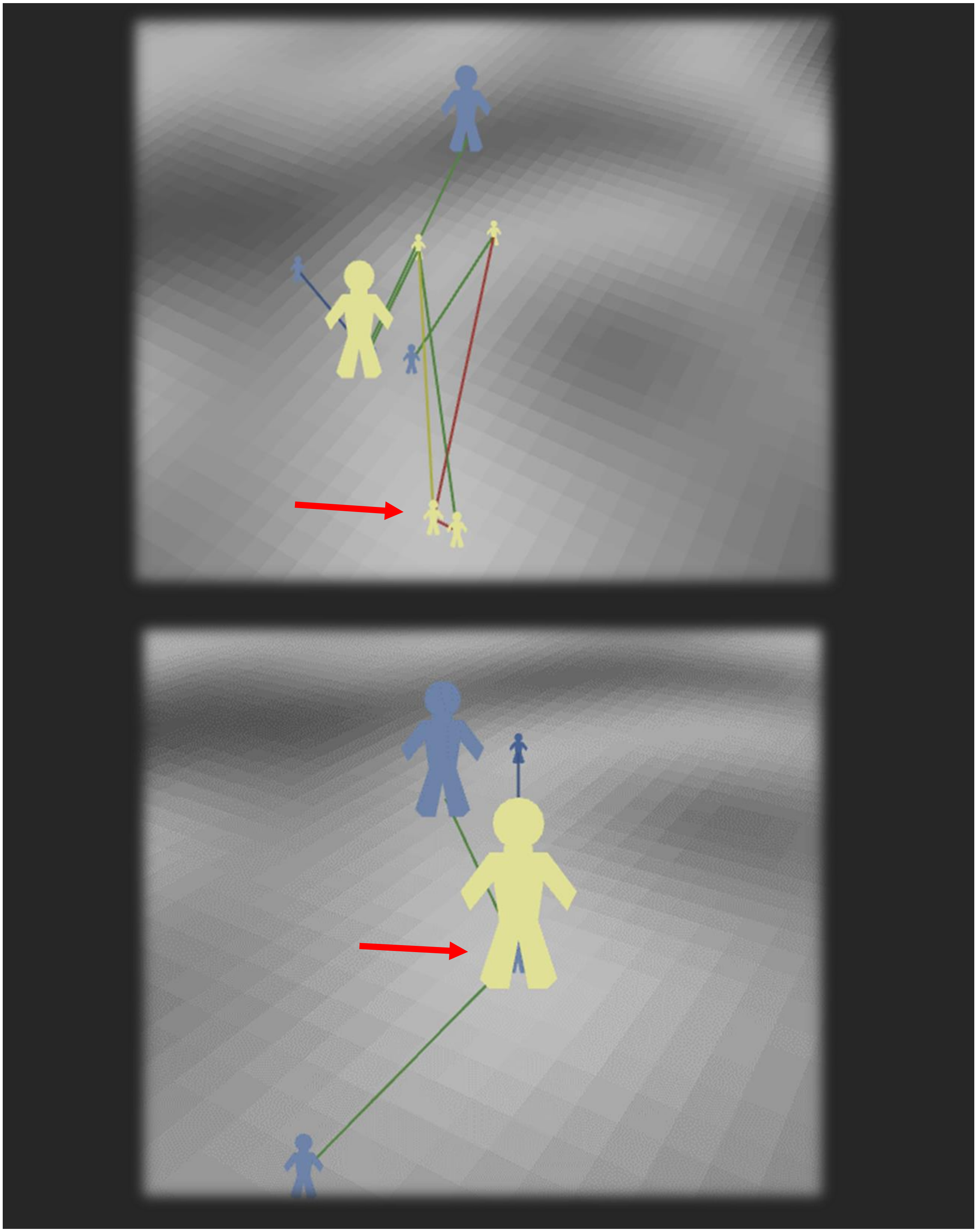


Figure 3.25 Hill Climbing to Local Optima. Collaboration members start climbing (top) towards the local optima in the C²D model, ending at the local optima (bottom). Arrow in the above figure represent the local attracting optimum.

3.3.5.1.4 Coalesce

Although design efforts may accept some level of diversity during its exploratory phase, when a design collaboration member finds a peak in the design landscape with sufficient fitness, the collaboration stops accepting diverse newcomers and switches focus from exploration to exploitation. The design collaboration does this to conserve resources, both time and physical, by maturing only a limited set of design options known to have sufficient fitness. This provides the collaboration the ability to minimize it search times by focusing the collaboration on the earliest design solutions discovered in its exploratory activities. This dynamics represents a base element of the C^2D meta-strategy (i.e. a defaulted element in the simulation). In effect, this coalesce dynamic reduces the maximum level of diversity for newcomers to zero (when a sufficiently fit ADMU exists) until the team coalesces around a single design solution. However, having a design take hold often takes time and even sufficiently fit design concepts do not always take wing. As a result, this strategy translates into only a temporary cessation of diversity for many cases. Commonly a design collaboration fails to anchor itself adequately to a design concept, as it takes some period for designers to grow an adequate coalition and sufficiently sized support network behind a concept. In these instances, as the last collaborators on these peaks disappear from the collaboration (either through aging or maximum downtime), diversity once again returns to the collaboration until another member of the DAU, through exploration, again finds the same peak or a different sufficiently fit design peak to exploit.

3.3.5.1.5 Require Consensus and the Same Stopping Point

Each point on the design landscape provides a singular and unique design conceptualization, with its own configuration of design parameters and functional requirements. The work of the design collaboration centers on not only moving the design effort towards fitness, but also on fostering consensus and moving the effort towards a singular design solution. For many instances, the majority of the time spent in designing complex systems, *i.e.* those with interdependencies, stems from these activities surrounding the construction of consensus and the negotiation of a design solution itself. Typically, these negotiations occur in the context of the typical allocation of technical design margins between the self-interested designers. Each of these designers must agree to a set of shared design parameters, representing an agreed to design approach for the functional requirements. Failure to come to a negotiated design approach, before moving onto a more detailed phase of design can result in costly future rework activities. As a result, the collaboration in the

C^2D model must enforce closure of the negotiation and consensus activities between designers. It accomplishes this by requiring each designer on the collaboration to occupy the same location on the design landscape (i.e. same configuration of design parameters and functional requirements) before terminating the design process.

3.3.5.2 Incorporating and Controlling Diversity on Design-Teams

Distance measures on the design landscape provide insight into the relative difference and diversity of design approaches. Similarly, we capture the notion of diversity via newcomers in terms of an allowable distance for the collaboration to recruit from, *i.e.* how wide is the collaboration willing to cast its net. These newcomers bring in their own unique insights, thinking, and background to the collaboration. They randomly enter the design landscape, often entering around unexplored areas of the design landscape. As these agents enter the collaboration, they provide a fresh perspective and new information about alternative possibilities for the design effort. These newcomers provide the biological equivalency of mutation and their distances on the design landscape from the recruiting designer, more specifically, correspond to the biological concept of mutagenic distance. Once an adaptation or mutation occurs at these locations, designers exploring one of these concepts have the increased ability to perform an adaptive walk towards increased fitness, increasing its likelihood to recruit new-team members along the way.[38] We consider strategies that dynamically control diversity based on the state of the current design collaboration. We compare these strategies to unique optimization models and representative of different approaches towards design. Each of these following concepts, although included by default in the model, represent independent strategies, *i.e.* we can control and test each individually.

3.3.5.2.1 Dynamic Diversity

Searches in the local neighborhood of a collaboration commonly result in insufficiently fit design solutions; in these instances, the collaboration considers increasingly diverse members of the design-team. In this strategy, the collaboration gradually increases its willingness to include diversity with time; in the implementation of this dynamic, we limit the growth of this diversity to

[38] As described in Chapter 4, the natural selection mechanism as actually implemented in the current C^2D model implements the natural selection mechanism strictly vis-à-vie a decreased probability for the expiration of an agent (i.e. resulting in more fit ADMUs having more opportunities to join a design-team). This same mechanism represents the basis of the management and technical leadership pressure mechanic when applied to a design-team; increasing this pressure decreases the threshold required for a design agent to probabilistically fall out of the collaboration.

the length of the diagonal of the design landscape, *i.e.* the maximum possible distance from any point to any other point on the design landscape. The amount of the increase of diversity at each tick depends on an analyst-controlled parameter labelled the dynamic diversity increase step. Notionally, the model defaults this incremental rise at each step to 0.030 patches, the unit of measure for distance in the C^2D model.

3.3.5.2.2 Stop Diversity if Fit

Communication between members of the collaboration help individual designers perceive its environment and the relative fitness of possible design locations. As the design collaboration matures and locates possible solutions, the collaboration can often discover that they, in general, have adequately fit design concepts to explore. In this event, the collaboration no longer requires continued exploration of the design space or diverse concepts; it transitions from its exploratory phase into an exploitation phase. In particular, when the average of the collaboration exceeds the fitness objectives set by the collective goals of the collaboration, this strategy eliminates all diversity for newcomers. In effect, this lack of diversity requires newcomers to align and cohere with an existing coalition of designers. Ideally, as discussed as part of the natural selection dynamic, the coalition of designers with the greatest fitness should, given enough time, more successfully recruit and grow their coalition; in effect, the team with the greatest fitness, can in general, outcompete less fit alternative design solutions. However, in the event that the average fitness for the collaboration falls beneath the fitness objective, for any reason, the design-team restarts any existing design strategy for diversity.

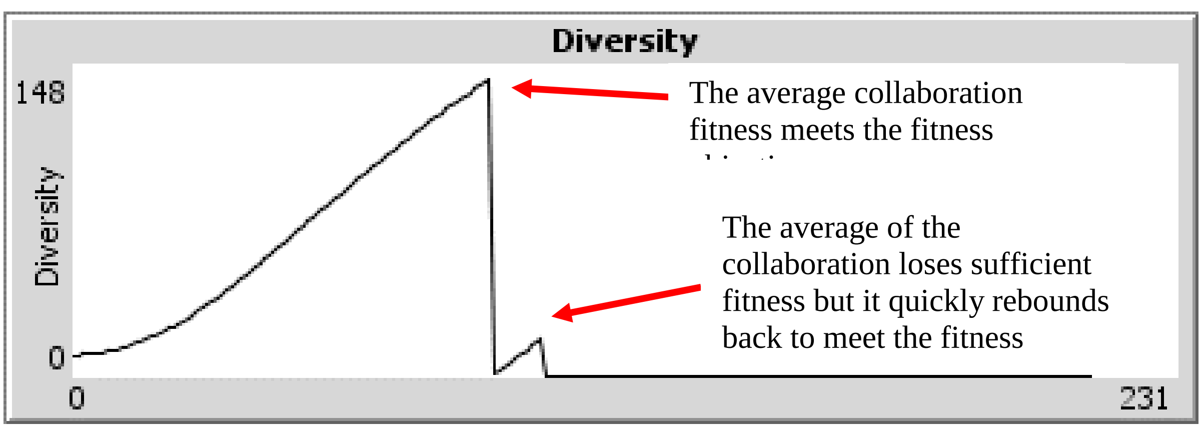


Figure 3.26 Ceasing Diversity as the Design Collaboration Achieves Fitness with Time (ticks)

General explorations of unimodal functions and their spaces can often follow simple techniques (e.g. linear fit models, polynomial fit models); engineering design, however, as discussed extensively provide much more challenging problems. Engineering design often represents complex multimodal problem spaces. Determining the modality and global optima for design landscapes, especially for those with high levels of interdependency, often cannot occur without a sophisticated search strategy. Broadly, search techniques and strategies for these problems include deterministic and random approaches. We have so far demonstrated the deterministic setting of maximum diversity levels via incremental increases, as well as the fact that the random placement of newcomers to the design up to this allowable deterministic limit. However, one clear limitation is that once diversity reaches its maximum limit the introduction of newcomers follows entirely from a random search strategy, which adds time to the search of the design space.

One strategy for managing the level of diversity over time includes varying the degree of diversity with time. One simple implementation includes having the collaboration, as before, start its exploration of the local neighborhood and gradually expanding its search to the furthest reaches of the design landscape. However, if the design process has yet to conclude successfully by the time it has reached a maximum diversity level that collaboration could reevaluate its current inventory of potential design solutions. To do so, we use this pause and restart diversity strategy to reset diversity to zero. This reset to diversity again allows the design collaboration to improve its understanding of the local neighborhood before attempting to locate new design solutions on the design landscape. This pattern results in a saw-tooth relationship between diversity and time. This sequential construction of the saw-tooth function allows the individual designers to converge gradually to the global maximum.

This approach interestingly mirrors optimization techniques, such as the Shubert-Piyavskii method for the optimization of non-unimodal functions (Shubert 1972). This optimization technique similarly uses a repeated saw-tooth to cover and explore non-unimodal functions. This technique proves generally sufficient for obtaining the global maximum of the design function, given sufficient time. We examine, as part of the experimental design, how this strategy as well as others contribute to both the final fitness and search times of a design effort.

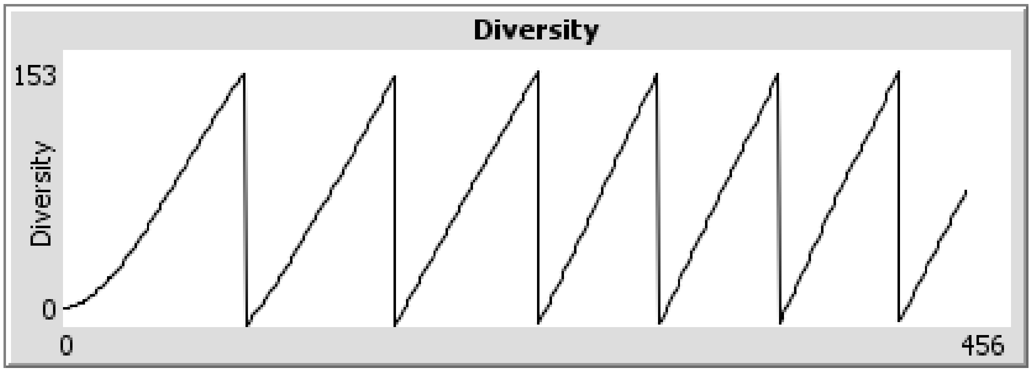


Figure 3.27 Pause and Restart Diversity Strategy with Time (ticks)

3.3.5.3 Stop Prolonged Decision-Making, Exert Management Pressure (λ_u)

The goal of any DAU management system with respect to performance revolves around the constant improvement of design fitness and the minimization of search times; in particular, the collective goal of a design collaboration seeks to, in the case of the C²D model, minimize search times while meeting performance objectives. Management of these efforts contributes to the collaboration environment for design; managers and technical leadership exert an abstract pressure (λ_u) on a collaboration as its progresses through the design process. Typically, this pressure grows as the design reaches viable solutions; it applies this pressure in order to prevent protracted technical exchanges and to drive the collaboration towards consensus. However, too much pressure or its unartful application can also lead to the collapse of a design effort. This strategy represents a meta-strategy built upon, and requiring, the natural selection strategy and dynamic discussed in Section 3.3.5.1.1. This strategy operates by gradually increasing the strength of the natural selection pressures in design. We test the effectiveness of this strategy as part of the experimental design.

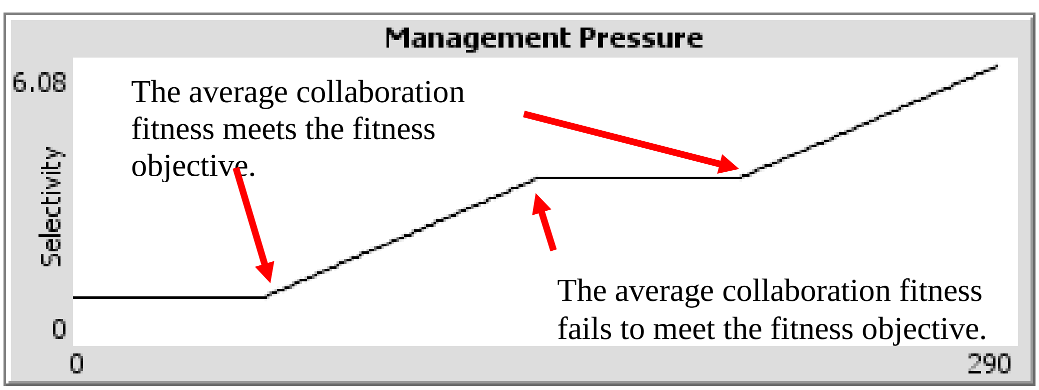


Figure 3.28 Management Pressure with Time (ticks)

3.3.5.4 Exploring Additional Strategies

Given the commonly large search space inherent to the design landscape, C^{2}D provides a platform to explore additional strategies to improve the search aspects of the design landscape. The following strategies represent some of the currently implemented strategies. Unlike the previously discussed strategies, these strategies default to off in the baseline C^{2}D model and represent opportunities for further development and experimentation.

3.3.5.4.1 Using Long Jumps to Overcome Valleys of Insufficiency

The goal of any self-interested designer in the collaboration revolves around the constant improvement of design fitness; however, this continually hill climbing process can often leave camps of multiple designers stuck in local optimum that fail to meet the fitness objectives of the collaboration. The long jump strategy forces designers at a peak, when not sufficiently fit, to jump a random distance up to the maximum distance for diversity. This maximum distance corresponding to the diagonal of the design space, *i.e.* a designer could jump from its local insufficiently fit optima to any other location on the design landscape at random.

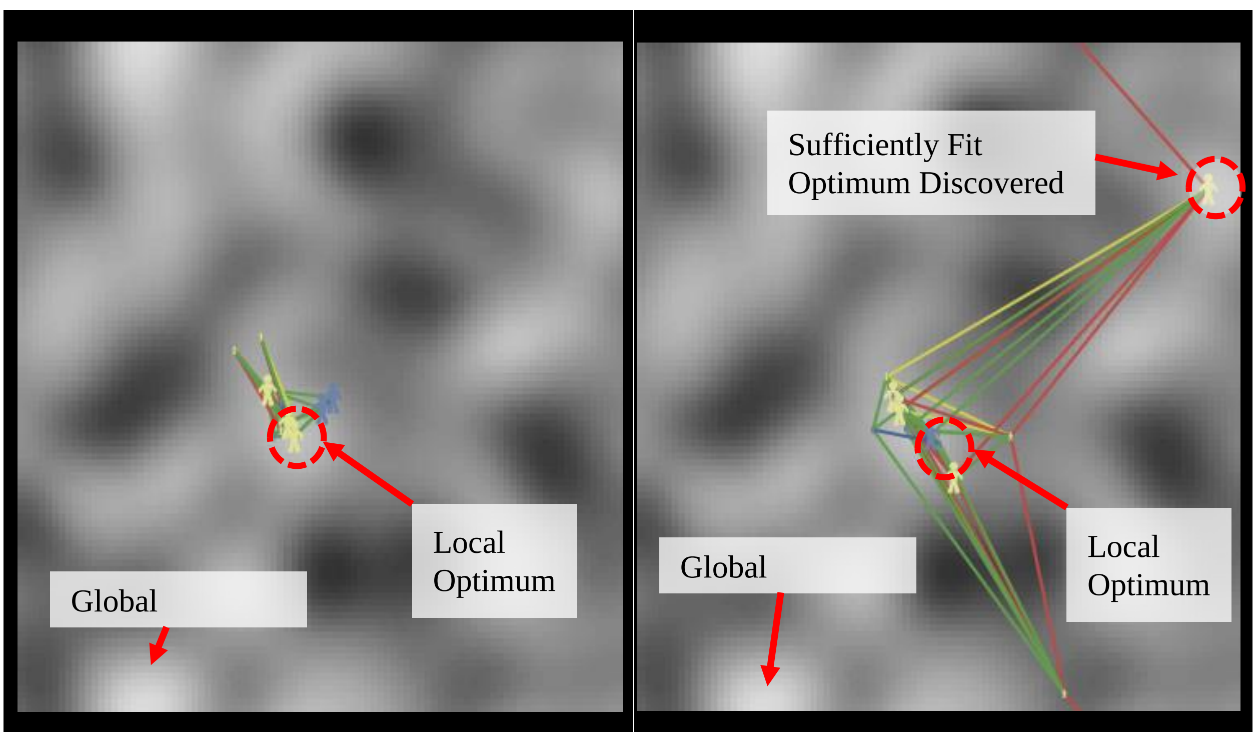


Figure 3.29 Comparison of General Hill Climbing (left) to Hill Climbing with Long Jumps (right). The red arrows in the figure point out the relevant optima. Under a long jump strategy, insufficiently fit attractors once reached are jumping off points. The resulting long jumps (up to the allowable diversity limit) allow the designers to move past large valleys of low fitness.

Some DAU collaborations could choose to limit diversity if presented with any designer of sufficient fitness, as opposed to waiting for the average of the collaboration similarly to achieve its fitness objective. In this strategy, we cease incorporating any level of diversity into the collaboration whenever any designer in the collaboration has a fitness value sufficient to meet the performance objectives for the design. During this period, the entire collaboration has an opportunity to explore the concept presented by the designer. This termination of the search procedure, given the discovery of a design solution that satisfies the minimum design criteria, provides a common terminating condition for many genetic algorithms. As such, we have included this stopping condition, which when used supplants the previous discussed diversity cessation strategy given in Section 3.3.5.2.2.

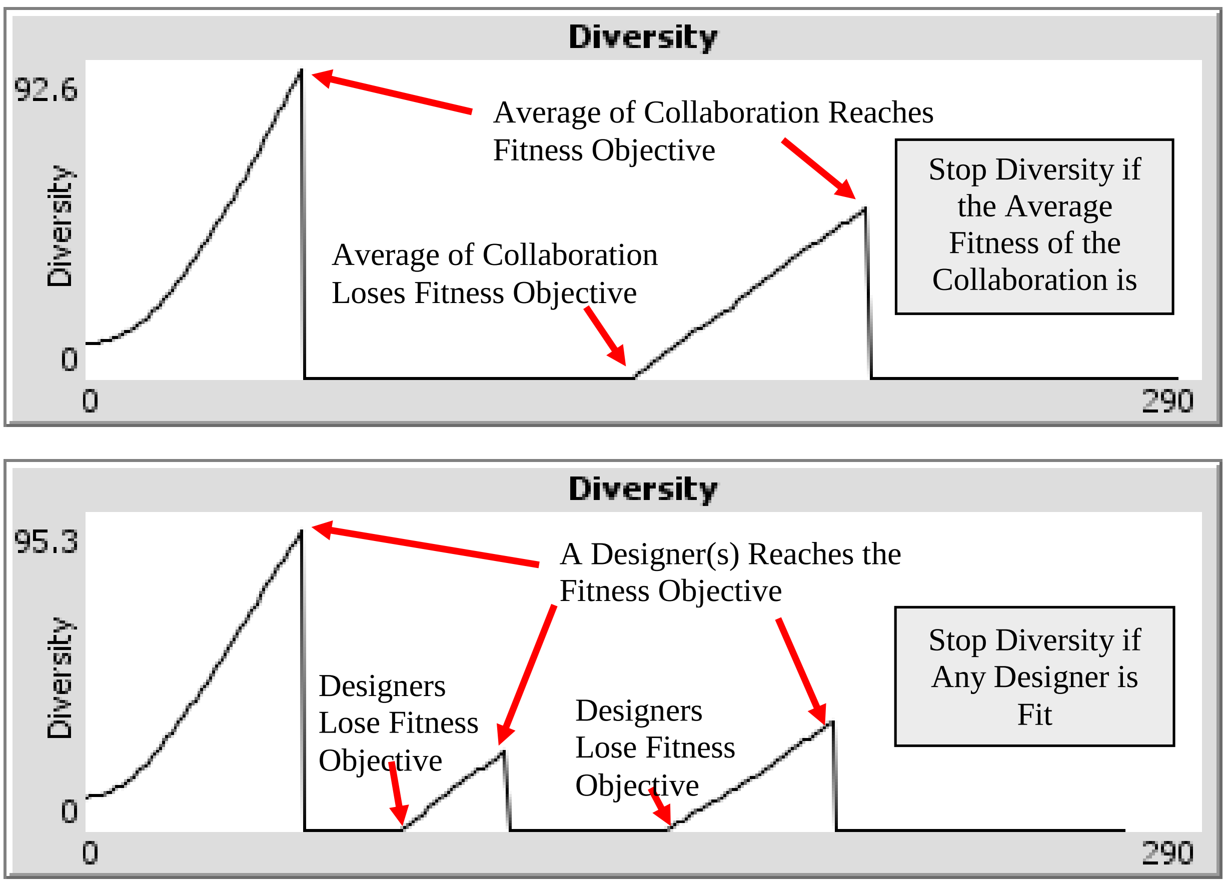


Figure 3.30 Limiting Diversity can Result in Differences in Search Times and Fitness. This figure demonstrates how different approaches for constraining diversity can result in differences in search times and fitness. The figure above highlights the use of the diversity cessation strategy that relies on the average of the collaboration (final consensus occurs after 284 ticks in the example). We compare that the figure below, which ceases incorporating newcomers when any designer achieves a sufficient fitness level. Similarly, the final consensus occurs after 270 ticks with the same design solution.

Self-interested agents must work in the context of the rules and strategies of the overall collaboration to facilitate the negotiations between designers and their consensus. Although the individual designers must work independently to maximize their own local utility, they must also follow design and collaboration rules to seek consistency with other designers (Bar-Yam 1997). In order to achieve this in C^2D approach we vary the composition of the collaboration to include agents, newcomers with varying diversity and fitness. Traditional simulated annealing approach enforces some number of agents, *i.e.* annealers, to accept lower performing fitness for temporary periods (Klein et al. 2003). We approximate this concept with the use of fitness measures and the mechanism of newcomers and their diversity as discussed throughout Section 3.3.5. The fitness measures parallel energy measures on a landscape in most simulated annealing approaches and diversity, similarly, represents the temperature of the system in this metaphor. Temperature remains a global time-varying parameter that provides the ability of a molecule or system to explore the potential energies or fitness of a landscape.

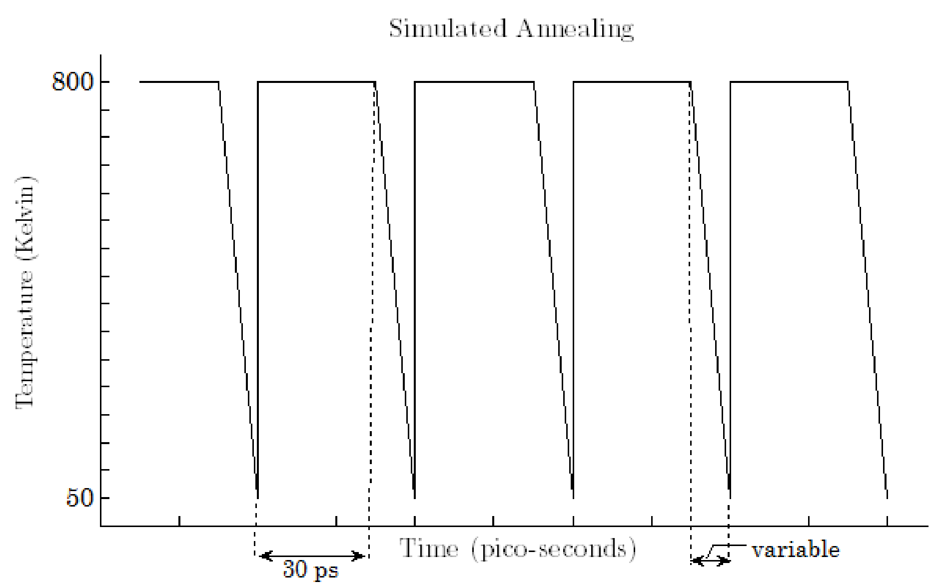


Figure 3.31 Example of Simulated Annealing in Molecular Mechanics. In this annealing example, we subject a molecular structure and its conformations to 30 picoseconds of dynamics at 800 degrees Kelvin. We then cool these molecules to 50 K over a variable period. By minimizing its energy, the molecule continually undergoes geometrically optimization and, through the repetition of this procedure, we realize the desirable material attributes from this heat-treatment procedure. The cooling step in the annealing protocol stands out due to importance in obtaining these desirable characteristics; the temperature drop has to occur and be sufficiently paced to ensure the appropriate equilibrium of the system.

We can improve on this annealing strategy in multiple ways; for instance, we can vary the diversity of newcomers in proportion to the relative nearness of the design collaboration in meeting design objectives. Loosely speaking, we implement this optional simulated annealing strategy by establishing this nearness as the average fitness of the collaboration relative to the fitness objective. In each implementation of this strategy, as time progresses we gradually reduce the resulting diversity to zero, resulting in a strict hill climbing strategy. Variation to this approach and its implementation can greatly influence the behavior of the model. The discussed implementation represents an initial attempt at studying the relationship between the self-interested members of the collaboration and the relative newcomers. The literature presents interesting and paradoxical considerations relevant to the study of negotiation of design activities (cf. Klein et al. 2002). This relationship between the interests of the collaboration and those of the self-interested collaborators provides a dilemma in many instances of design. The negotiation that occurs between incumbents and newcomers parallels this “prisoner’s dilemma” from game theory as described by Osborne and Rubinstein (1994) and Klein et al. (2003). Table 3.13 summarizes the findings from Klein et al. (2002), which show that while annealers (in our case newcomers to a design) increase global fitness, they individually fare worse than hill-climbers (in our case incumbents) if present in a simulated non-linear negotiation. The results also show that hill climbing remains a dominant strategy. We use newcomers to provide a degree of annealing to the base C^2D model. We also allow the natural selection component to help mediate negotiations. However, a more direct implementation of simulated annealing as a strategy asks a random set of the designers to assess the fitness of accessible random neighbors. In this implementation, if the random accessible neighbor represents a fitness improvement the designer moves locations.

Table 3.13 Prisoner’s Dilemma between Agent Strategies, results from Klein et al. (2002)

[<global fitness optima>] <fitness 1> / <fitness 2>	Incumbent 2 (hill-climbs)	Newcomer 2 (anneals)
Incumbent 1 (hill-climbs)	[.86] .73/.74	[.86] .99/.51
Newcomer 1 (anneals)	[.86] .51/.99	[.98] .84/.84

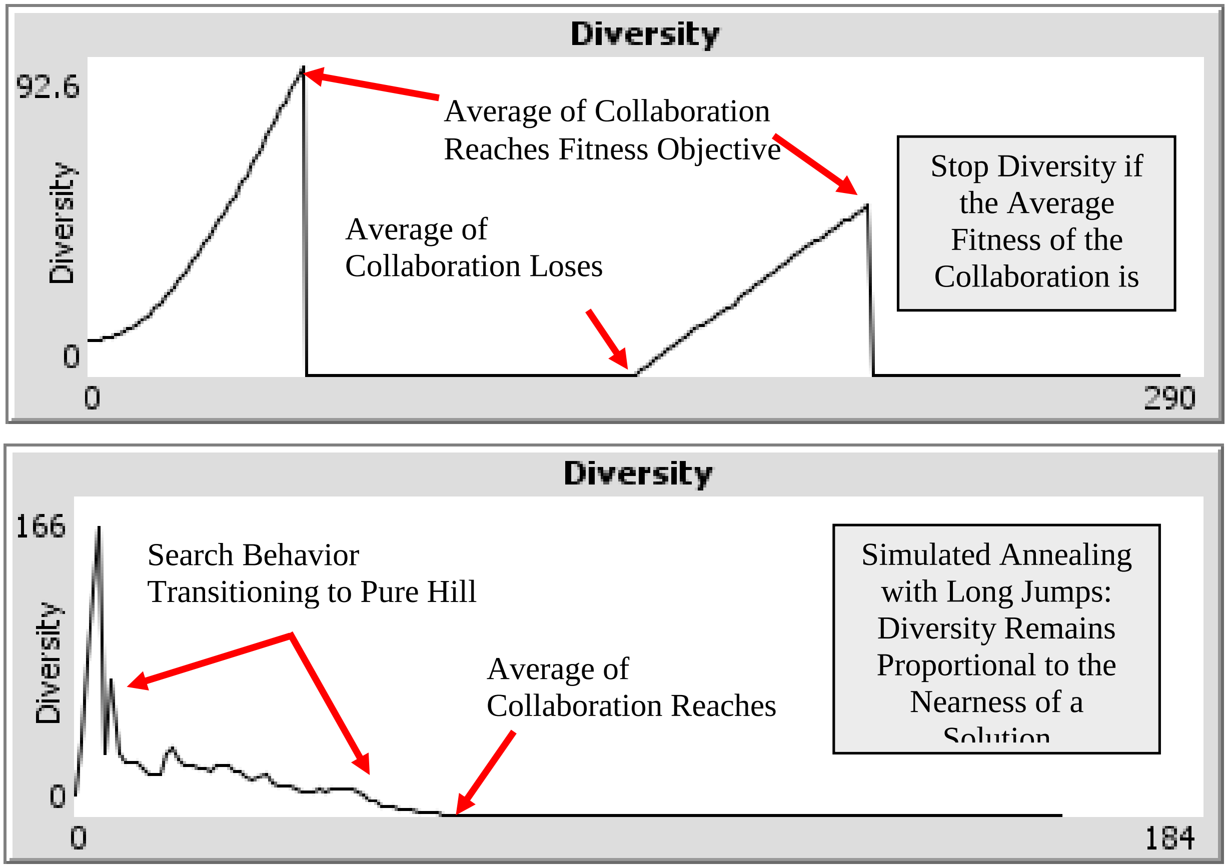


Figure 3.32 Different Conditions for When and How to Limit Diversity Can Result in Differences in Search Times and Fitness. The figure above highlights the use of the diversity cessation strategy that relies on the average of the collaboration (final consensus occurs after 284 ticks in the example). We compare that to the figure below, which gradually diminishes the diversity of newcomers in relative proportion to the nearness of the collaboration average fitness with respect to the design fitness objective. Similarly, the final consensus occurs after 161 ticks with the same design solution. Each example throughout Section 3.5 similarly used v3.5.3 of the model with the same parameters $n = 5$, $p = 42\%$, $q = 85\%$, $mdt = 40\ ticks$, $S = 42\%$, and a constant $Seed = 2436$.

The accessibility of neighbors depends on the acceptable diversity of the collaboration; it in essence provides the temperature components in the C^{2}D implementation. As time progresses, the number of accessible designers for comparisons diminishes. This parallels the gradual cooling of a system, hence the annealing algorithm namesake. Our approach and the resulting model behavior closely approximates most implementations of the simulated annealing algorithm. For example, most simulated annealing approaches similarly begin by probabilistically deciding to move an agent to a new state location or to remain at its current state depending on a transition probability. Through a series of comparisons to neighboring energy levels, fitness in the case of C^{2}D, the system gradually moves to a global optimum or a fitness position that suffices its fitness objective.

These approaches govern the movement of agents to neighboring positions based on acceptance probabilities, as in the C^{2}D implementation. Similarly, the C^{2}D implementation gradually reduces the number of comparisons over time. This gradual reduction corresponds to the annealing process, where the gradual cooling of a system reduces its energy and the ability for molecules to reconfigure themselves. As in parallelizable versions of this algorithm, C^{2}D runs this process for multiple designers at the same time to overcome any deep local minima on the design landscape.[39]

Future work could provide substantial improvements to this strategy and potentially reduce search times for designers and their collaborations. Building upon the work and negotiation suggestions from Klein et al. (2003) provides multiple considerations relevant to potentially providing insights into how to create win-win environments for the designer and the design collaboration. One possible avenue for future work includes incorporating a reputation dynamic among designers regarding their cooperativeness and ability to anneal their individual fitness for the benefit of the overall fitness of the DAU collaboration. From a management systems perspective, this could provide real-life opportunities for improvements to the design process. For example, it could highlight the benefits of improved and transparent feedback from peers. From a theoretical perspective, the actions of designers do not currently depend on the cooperation of other designers in the implementation of the model; however, the inclusion of a reputation dynamic augments the set of percepts available to an individual designer in its decision making-processes. The incorporation of this reputation dynamic would allow for designers in the current C^{2}D framework to decide, over time, with whom to cooperate with and move to on the design landscape. Future efforts could further expand upon these relationships by allowing multiple designer types (e.g. subsystem representations) each with their own unique fitness landscape. Although we currently

[39] This corresponds in the literature partially to the parallel tempering process or replica exchange Markov chain Monte Carlo (MCMC) technique (cf. Swendsen and Wang 1986; Geyer 1991; Falcioni and Deem 1999; Earl and Deem 2005). This technique similarly runs N multiple parallel search points randomly initialized and at different temperatures; further, this technique allows for the communications between systems at their various states. It follows the Metropolis criterion in its decision-making. This criterion follows from the following two rules: 1) if the change in potential energy (ΔU) remains less than zero, accept the move; and, 2) if the change in potential energy exceeds zero then accept the move only if the probability of acceptance P^{acc} given by $e^{-\Delta U/T}$ exceeds a random value r drawn on the interval $[0,1)$. In the C^{2}D model this probability of acceptance P^{acc} follows from the fitness f_d of the designer, where r follows from a random uniform-normal draw on the interval $[0, f_{d*})$ where f_{d*} corresponds to the fitness of another randomly drawn designer within the allowable diversity range. This allowable diversity range similarly corresponds to temperature in the simulated annealing metaphor. However, unlike the full MCMC technique the temperature component equivalent of maximum diversity remains uniformly applied to each designer in their search.

treat the design landscape as a shared fitness landscape by each of the designers, the expansion of multiple fitness landscapes and the gradual emergence of a shared value model among collaborators represents an area of great potential for future research efforts.

3.3.5.4.4 Expanding on Potential Strategies for Design

The focus of this research centers on exploring how the collaboration itself, specifically the way formations form, influences the performance of design-teams. However, we have discussed several prominent optimization and search strategies with the hope of finding design approaches and behaviors that can improve and incentivize an overall design environment suited for the successful collaboration of engineers and designers. We have discussed techniques for also improving the individual search performance of designers. Nevertheless, the C^2D model provides a conceptual platform and framework capable of testing an infinite number and combination of design strategies. For example, the C^2D model, in addition to the strategies discussed above, could also provide a basis for testing strategies that vary team-formation parameters dynamically around the progression of a design. For this initial research, we limit the scope of the research by establishing the team-formation parameters as the experimental variables. In future work, we foresee using the experimental findings to refine, develop, and create strategies to incentive the growth of design collaborations themselves. Further, we could introduce observed data or trends in lieu of making these parameter experimental variables. These improvements could further promote and aid the design process in reaching its goals both efficiently and effectively.

Each strategy discussed, including the possible extensions in the future, correspond to real-world possibilities. For example, the use of varying diversity not only corresponds to hiring practices and deliberative approaches to managing matrix organization, but also provides insight into when to bring in outside subject matter experts to review the progress of a team. The concept of management pressure, similarly, provides insight into developing appropriately structured management systems around the design process. These strategies all remain essential elements in understanding and overcoming the current limitations of design approaches. Understanding the importance of tracking the behaviors of individual designers, and their willingness to consider design alternatives represents a central challenge for managing design. The essential benefit of this line of research remains the ability to describe, examine, understand, and test the limitations of existing or theoretical design approaches in an overall framework.

3.4 C^2D Framework for Studying Design

Despite important advances in fundamental technologies, many design approaches continue to remain relatively locked-in to the use of outdated technologies. The C^2D framework demonstrates through analogy that as a design grows increasingly complex and design decisions increasingly intertwined, the weight of design decisions grow in temporal significance. In other words, the influence of early design decisions, as shown through the initial movements on the design-landscape, correspond to increasingly affixed design positions; these positions carry with them design ramifications well into the future through its design variants and improvements. Consider the case of the Boeing cited by Klein et al. (2003), where despite many important advances (e.g. engines, materials, avionics) the design approach over the previous 30 years of commercial aircraft development within Boeing remains relatively unchanged. In other words, despite important advances in aeronautical engineering and material science, aircraft design continues to remain locked into its position on the design landscape, relying on the same basic design concepts and approaches that made it successful in the past. While past success provides a known executable path, this also creates systemic stickiness in design approaches moving forward. In the context of C^2D, this stickiness similarly represents beginning the redesign process from a known neighborhood on the design landscape, leading to incremental changes of a limited nature often bounded by persistent local optima. Arrow (1963) refers to this occurrence of "history matters" in its broadest sense as a form of path dependence, and, its strong form, he refers to this historical overhang as a source of inefficiency. In engineering design, the same phenomena remain a critical and relatively understudied consideration that touches every complex system design. As systems become increasingly complex, under the assertion of this research, the role of path dependence becomes an increasingly larger concern. Going from incremental design improvements to radically innovative design concepts will require substantial changes in design processes and design thinking. The C^2D framework and model provides an approach for evaluating the influence of these factors. Specifically, C^2D provides a unified framework relating technology and complexity, team-formation parameters and collaborations, search strategies, and team-performance. We summarize these foundational relationships in the following tables. We begin by relating aspects of technology to the design landscape in Table 3.14-3.15. We then transition to summarize the key nature of collaborations and teams as they relate to design in the C^2D framework.

Table 3.14 Design Technology Characteristics and their Impact on the Design Landscape

Structural and inherent artefact complexity	**Landscape Topology Relationships**
Number of functional requirements (N) in a design. In the event that functional requirements have redundancies (*i.e.* the number of design parameters exceed the number of functional requirements), we consider each redundancy as a separate requirement to the design.	The size $[A^N]$ and dimensionality $[N(A-1)]$ of the design space, a combinatorial search space, depends on the number of functional requirements. As implemented, we consider only two states (i.e. $A=2$); these states denote the existence or absence of a relationship to a design parameter. The overall size of the design landscape represents a measure of the number of these functional requirements.
Complexity of an engineering design approach ($0 \leq K \leq N-1$)	The design landscape ruggedness represents the relative interconnectedness of functional requirements in a design approach.

Table 3.15 Design Landscape Characteristics and Associative Inferences

Landscape Characteristic	**Associative Inference**
Locus (current patch)	Each location on the landscape represents a unique design approach, a particular combination of design parameters and functional requirements.
Distance (patches)	A measure of difference in design approaches. This measure provides a conceptual correlation to the required effort, *i.e.* the greater the distance the more effort required by a design collaboration to achieve a solution. In its implementation, distance equates to the Hamming distance (i.e. number of positions at which a location on a binary NK string describing a design differs for another specified location).
Height (fitness)	The design landscape height (also implemented as gradient shading) provides a representation of fitness (i.e. design value). The greater the fitness the greater height (also brighter) of the patch.
Fitness peaks	Fitness peaks represent optima, either local or global, with regard to the design approach.

In addition to the technology aspects of representing a design landscape, C^2D more important explores engineering design as a collaborative effort. We highlight specific aspects and parameters of these collaborations most relevant to the C^2D framework in Table 3.16 and Table 3.17.

Table 3.16 Design Collaboration Attributes and Associative Inferences

Collaboration Attributes	**Associative Inference**
Collaboration	Almost all complex artefacts created today result from the interactions of multiple, often spanning thousands, of designers. The design process relies on the interactions of these collaborative interactions to support, inspire, and evaluate the work of ongoing design. The collaboration represents a network of previously engaged that provide a pool of expertise and potential for design-teams to draw from.
Design-team	Design requires iterative and recursive problem solving. The design process, as a result, requires the focused effort of a group of designers to solve the current problems associated with the design. This group forms the basis of the current design-team who may include, depending on their willingness, designers from outside of the existing collaboration.
Newcomers	Design-teams may often include new designers originating from outside of the current collaboration. These members bring their background and diversity of thought to the team in its assessment of the design problem. However, they are also inexperienced with regard to the collaboration.
Incumbents	Design-teams may include experienced collaborators who have participated as part of the design-team more than once in the past. These collaborators and designers bring to bear both the knowledge and biases of their past to the problem.
Diversity	Each designer brings to the collaboration different perceptions and understandings of the design problem. We treat diversity as a dynamic measure of differences in design approaches among designers, as measured by distance in the design landscape.

Table 3.17 Design Collaboration Parameters, Related Characteristics, and Associative Inferences

Collaboration Attributes — **Associative Inference**

Team-size (n)

The number of design-team members selected to tackle the current design tasks.

Probability of a newcomer (p)

The likelihood of a incorporating a newcomer into a newly formed design-team.

Propensity to repeat (q)

The likelihood of a designer on a newly design-team to repeat a collaboration with a collaborator of the previous team.

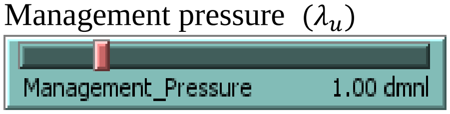
Maximum downtime (mdt)

The allowable amount of time for a designer to remain part of the collaboration without being selected to participate in a design-team. If a designer remains on the collaboration beyond this maximum downtime, the designer decides to leave the collaboration.

Maximum diversity (m)

Each design-team must also decide how divergent of concepts they are willing to pursue; they do this through a maximum diversity level for all newcomers to a collaboration.

Management pressure (λ_u)



As each design matures, the management can decide to increase its selectivity with regard to how many designs alternatives it is willing to pursue. This factor in essence increases the selectivity of the natural selection dynamic of the C^{2}D model by causing designers to leave the collaboration quickly through an accelerated aging process of designers.

*Age**

Each designer also has an aging component. If a designer has explored insufficiently fit designs for too long, the collaboration removes these designers and their underperforming design concepts from the collaboration network.

*Fitness**

Each member of the collaboration has a fitness score, this score corresponds to the relative merits of the design concept currently occupied on the design landscape.

We utilize these parameters to explore how designers come together to collaborate and explore complex design spaces. We view these fundamental explorations through the context of searches on the design landscape. We examine the characteristics of these searches in terms of the following core concepts highlighted in Table 3.18. By integrating each of these core considerations, we in essence arrive at the general C^2D framework. We provide an overview of the resulting C^2D framework and model in Figure 3.33 and Figure 3.34.

Table 3.18 Characteristics of Searching the Design Landscape, Inferences, and Relationships

Search Characteristics	**Associative Inference and Relationships**
Design objective	The collaboration sets the objective for the design effort, which in the case of C^2D includes a constrained minimization problem for search times. More specifically, the objective of the collaboration is to minimize the overall search time while meeting minimum fitness levels. Individual designers execute on this objective by working to maximize their individual fitness values.
Overall search time	The amount of time required for the collaboration to achieve a design consensus around a design concept with adequate fitness.
Search rate	Each designer in a collaboration can only explore one concept at a time. This translates into an exploration rate of one patch per tick per designer. Finding strategies to support larger collaborations can help to improve the amount of search activity possible for a design effort, but it also can increase the time required for reaching consensus.
Search distance and direction	In general, each designer in a collaboration can only move in single patch increments, *i.e.* a hamming distance of one. However, strategies such as using long jumps can also enable designers to explore concepts far away from their current conceptual approach. In general, the direction of a search occurs at random for newcomers to a design and follows from the strategies of the existing collaboration members. Each member of the collaboration follows internal goals to achieve fitness by following an adaptive hill-climbing strategy. This strategy in turn governs the direction of the search for the design collaboration.

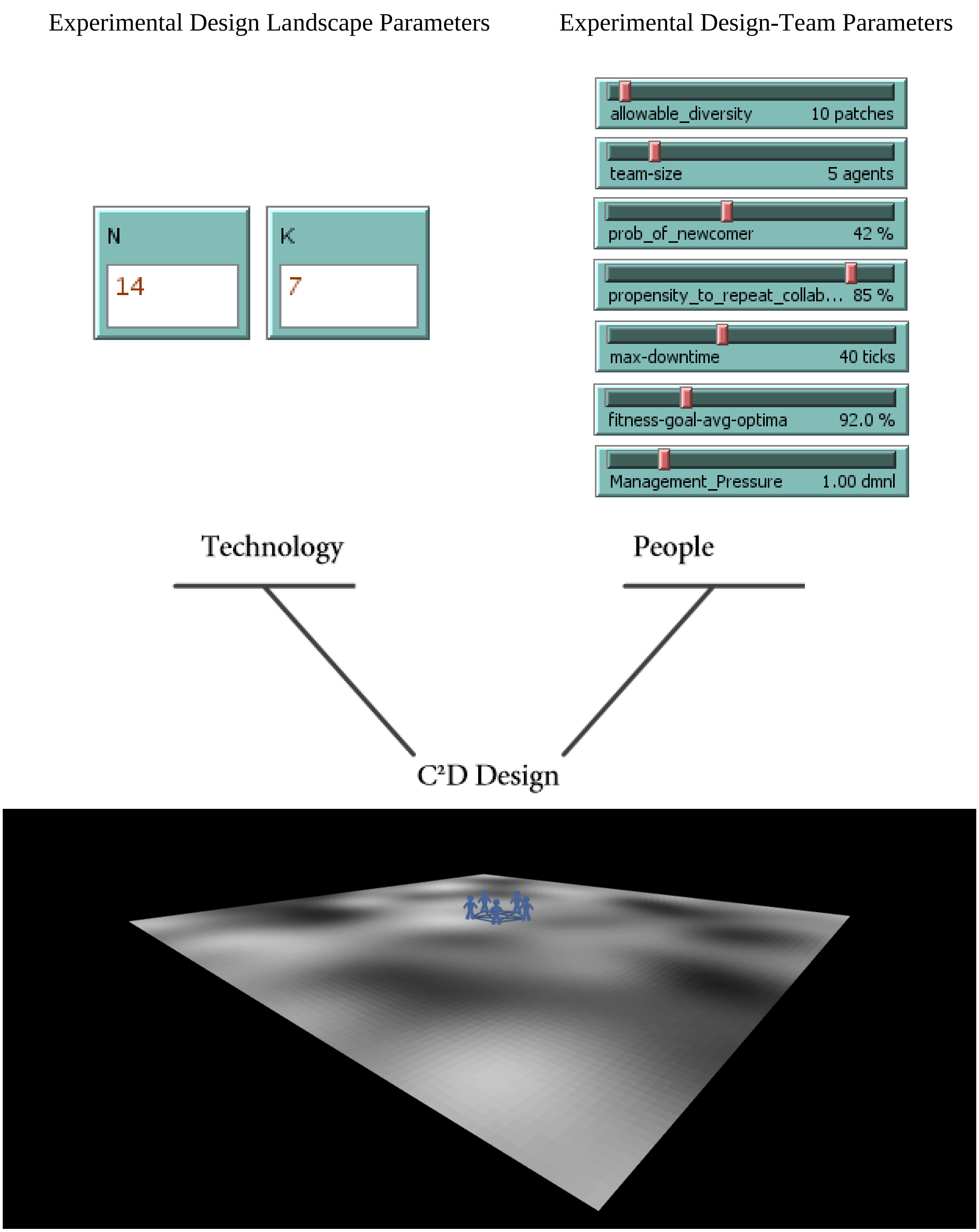


Figure 3.33 C²D as a Socio-Technical Model. This figure demonstrates how the C²D model combines all of the technology and team concepts into the singular framework. This unified platform allows the analyst to explore the factors and dynamics inherent to engineering design performance, encompassing both design complexity and design-teams.

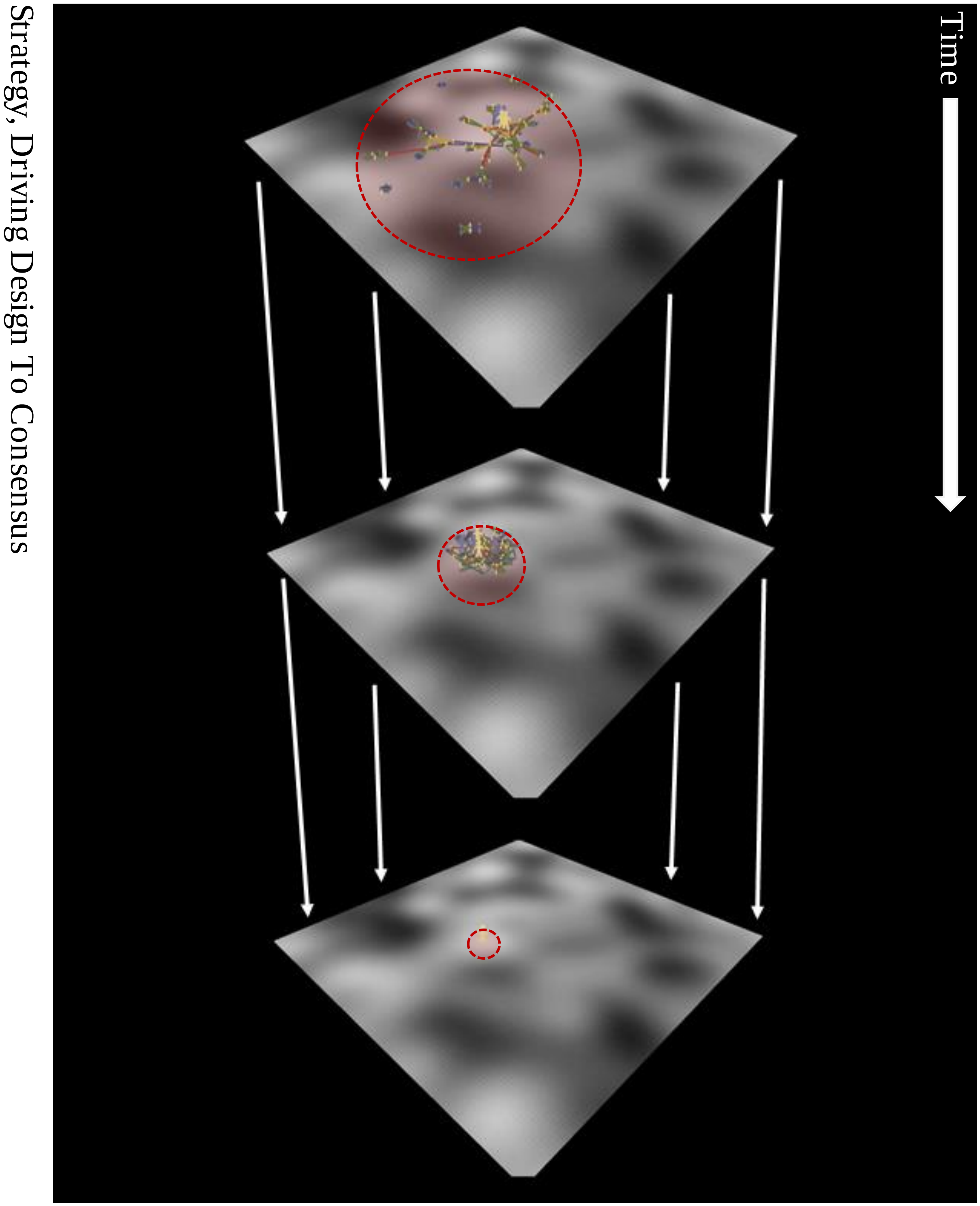


Figure 3.34 Strategy Driving the Design-Team to Consensus. The mechanisms driving the simulation of design center around the use of design strategies (cf. Section 3.3.5). In order to come to an agreement the collaboration must eventually occupy the same design locus (i.e. design concept). Dashed circle represents the neighboorhood of exploration by the collaboration. We spring-out at the generation of each graphic the network for visualization. Eventually this exploration leads the collaboration to a singular local optima that the all collaborators eventually climbs toward and finally coalesce around through consensus.

3.5 Potential C^{2}D Enabled Insights

By treating the DAU system as a collaborative human ecosystem and as a *complex adaptive system*, this research explores the autonomous, goal-oriented, non-linear nature of human decision-making units in engineering design. The inductive complexity science based approach towards design and design-team performance allows this research to establish an alternative to the traditional deductive design science approaches for understanding and measuring design performance. The C^{2}D framework and approach provides a method to develop insights regarding design performance and a platform to test potential improvements that promote an environment supportive of the creative and technical work of engineering designers. Additionally, it provides insights regarding the emergent behaviors in design and further elucidates the "indirect" and unintentional effects caused by interdependencies and feedback loops in the exploration of design possibilities. We showed in the previous section a representation of design as the exploration of a theoretical technology possibility space by design-teams. We introduced the concept of a *design landscape* to represent this space of all possible designs. Linking this design landscape to the design-team in a singular framework as highlighted in the previous section provides for an overall framework for understanding design performance. Ultimately, the quality and nature of the derived relationships and insights arise from the run of multiple simulations and its resulting data. Therefore, we first examine the types of data collected before proceeding to a brief overview of the possibilities for insight generation.

3.5.1 Data Generated

The platform used for the C^{2}D simulation, NetLogo, provides the ability to easily capture and record all relevant data over the course of multiple simulations. We will discuss the data captured broadly in terms of search performance and fitness data, landscape exploration characteristic data, collaboration network properties data, and strategy driven experimental data. We will highlight the most relevant types of collected data through both graphical means and the potential measurands collected from the simulation.

3.5.1.1 Search Performance and Design Fitness Information

One of the most fundamental attributes to the C^{2}D simulation centers on capturing the relative merits of a design concept, *i.e.* the design fitness. We capture the fitness characteristics through multiple direct and supporting measurands. We first capture the search performance characteristics in terms of the time spent during design, including the time spent during design exploration and the design consensus processes through the following measurands:

- Time for the design-team to reach its final stopping-position on the design landscape;
- Time for the collaboration to reach its final stopping-position on the design landscape; and,
- Time spent in consensus

We also capture the performance characteristics of the collaboration members in terms of measurands with regard to fitness, with the:

- Minimum fitness of all designers;
- Maximum fitness of all designers;
- Average fitness of all design-team members;
- Average fitness of the overall collaboration;
- Approximate fitness, *i.e.* mean of the averages for collaboration and deign-team fitness;
- Average fitness of the incumbents in the collaboration;
- Average fitness of the newcomers in the collaboration; and,
- Average fitness of the current design-team

Similarly, we capture the fitness characteristics inherent to the design space with the:

- Minimum fitness of the design landscape;
- Maximum fitness of the design landscape;
- Average fitness of the design landscape; and,
- Quantity and average fitness of the local optima (i.e. peaks) on the design landscape

These inherent design space characteristics allow us to calculate, through the stopping rule, the stopping-fitness for the average of the collaboration. Additionally, we represent the relationships of most interest graphically. We demonstrate these graphs in Figure 3.35.

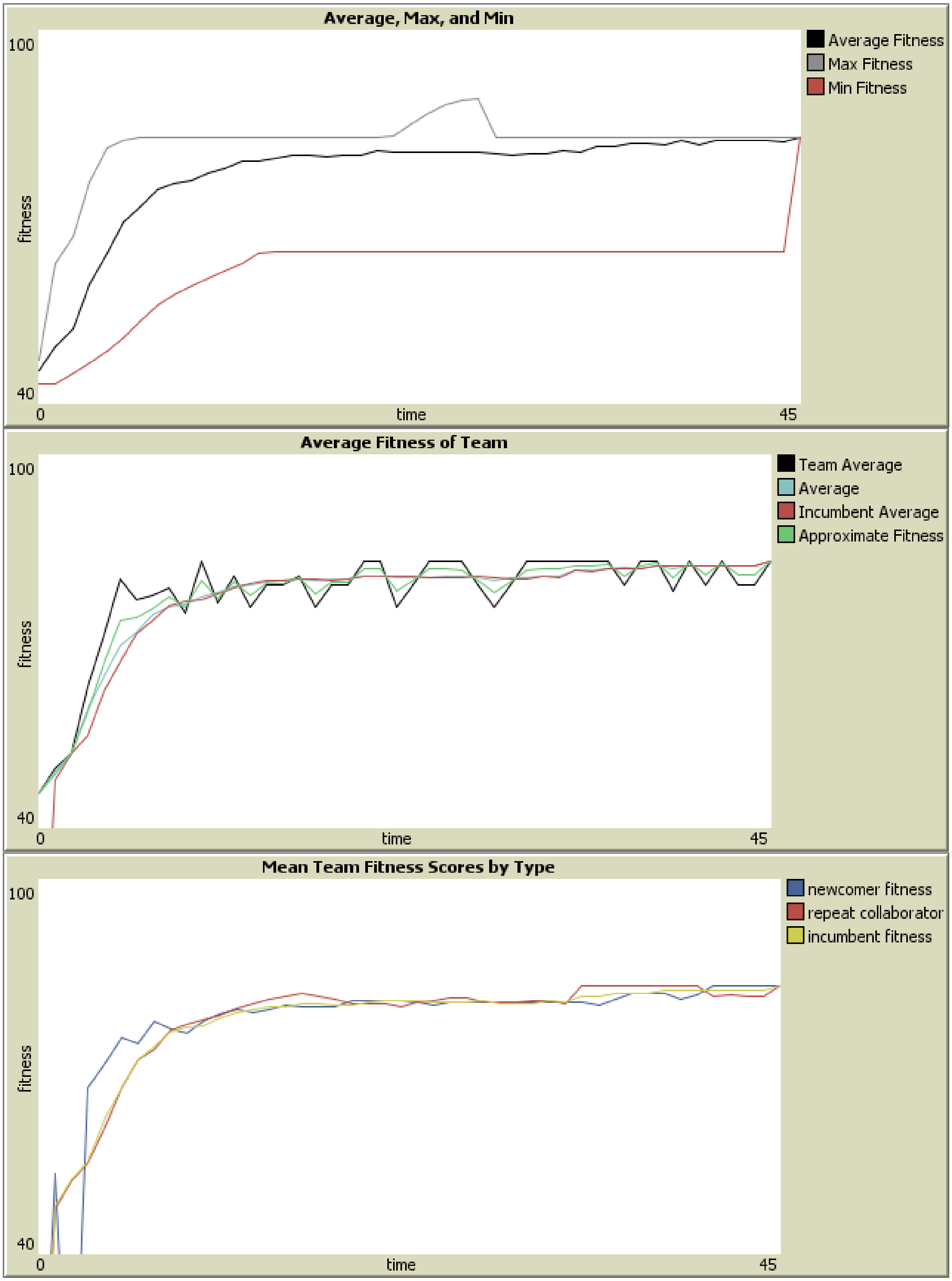


Figure 3.35 Graphical Representations for Fitness in C²D

3.5.1.2 Characteristics of the Landscape Exploration

As designers explore the design landscape in the C^2D simulation, their discovery of optima and more generally of improved fitness locations become important performance indicators. As done with fitness specific measures, we similarly capture these characteristics of the exploration of designers through multiple direct and supporting measurands, including the number of:

- Collaborators who have improved their fitness from the previous tick;
- Improved design locations currently explored by at least one collaborator;
- Optima (i.e. peaks) currently occupied by at least one collaborator;
- Collaborators currently on an optima; and,
- Collaborators currently on the global maximum

As before, we also represent the relationships of most interest graphically. We demonstrate these graphs in Figure 3.36 and Figure 3.37.

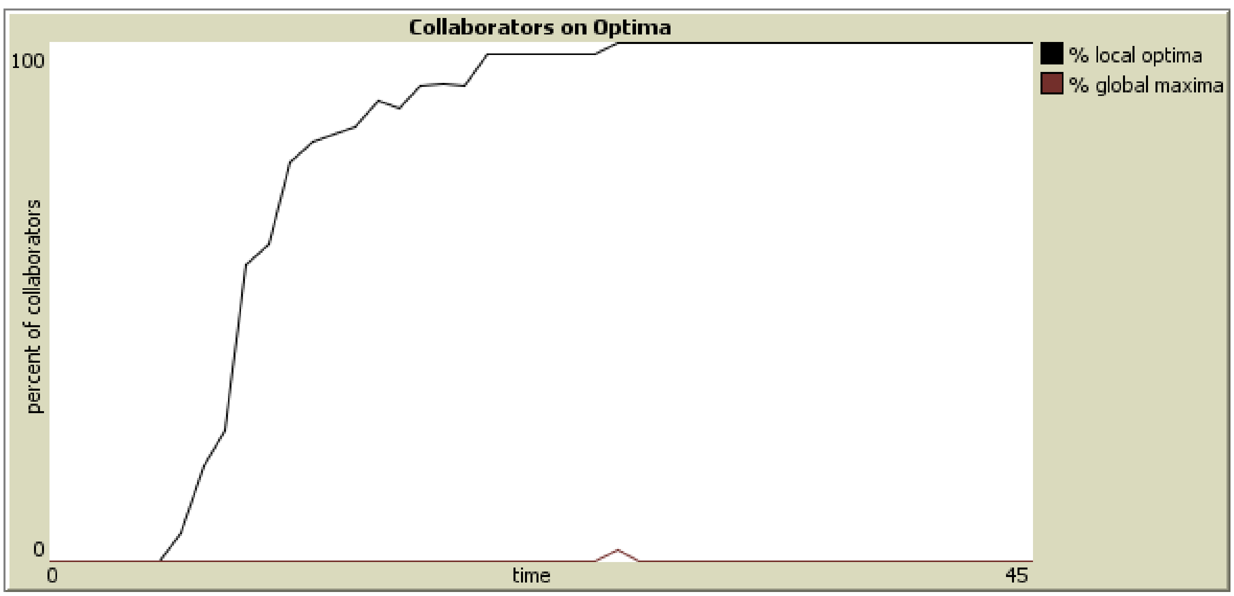


Figure 3.36 Graphical Representation of Collaborators on Optima. Visualizing the percentage of turtles currently on optima provides insight into the rate of convergence of the design collaboration around a design concept. We separate out local optima from global maxima to demonstrate and capture how, although at one point in time a designer in the above example did reach the global maxima, the coalition surrounding the existing local optima had a larger influence in the outcome of the final design selection. We can examine this, as well as the other graphs, for patterns or emergence given various configurations of experimental parameters, including the ruggedness of the design landscape. Each of the graphs for Section 3.5.1 were generated using C^2D v3.5.4.1_figures with the same parameters $n = 5$, $p = 42\%$, $q = 85\%, mdt = 40\ ticks, S = 73\%$, and a constant $Seed = 5532$.

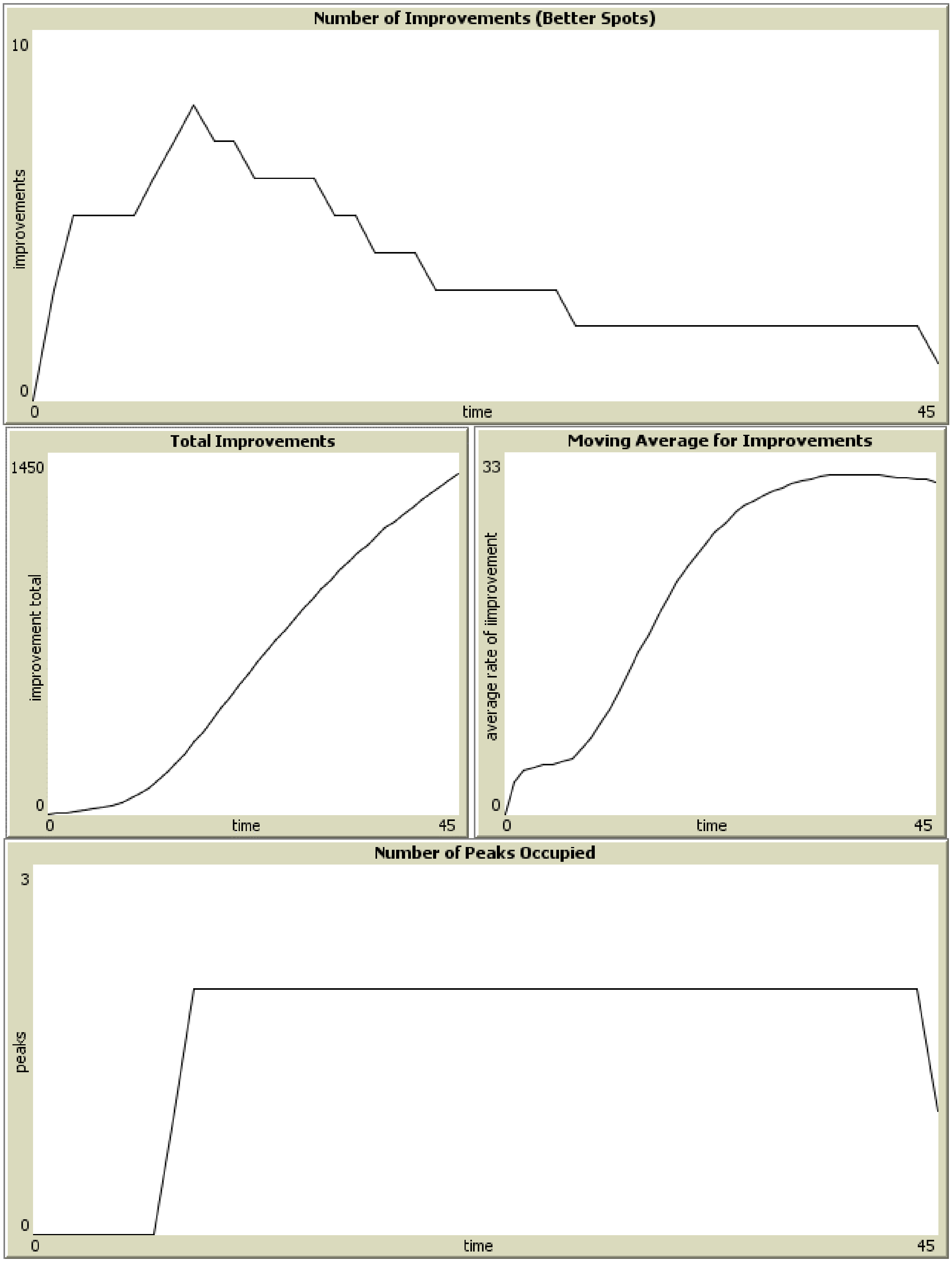


Figure 3.37 Key Graphical Representations for Landscape Exploration in C²D

3.5.1.3 Collaboration Network Characteristics and Composition

An essential element to the C^2D concept is the collaboration and its composition. In the research, we examine the roles of team-formation parameters in the performance of the collaboration, both with regard to the effectiveness of the collaboration in finding design solutions and its efficiency as measured in the time spent searching. The C^2D model demonstrates how the individual decisions of designers to preferential attach and collaborate with either newcomers or incumbents at the start of each generation or increment of time greatly influences these performance measures. In order to answer and further explore these concepts and the hypotheses posed as part of Chapter 1, we capture this performance data for a wide range of collaboration measures. These measures help to describe the collaboration and its changing nature and composition. As done with the previous factors discussed, we capture these data at each increment of time. For the collaboration composition, these data include:

- The number of inexperienced newcomers in the collaboration;
- The number of seasoned incumbents in the collaboration;
- The number of seasoned incumbents currently repeating a past collaboration;
- The number of inexperienced newcomers on the design-team;
- The number of seasoned incumbents on the design-team; and,
- The number of seasoned incumbents on the design-team repeating a past collaboration

The information also characterize the nature of relationships between collaborators and design-team members, by including the following linkage data:

- The number of newcomer-newcomer links (blue);
- The number of newcomer-incumbent links (green);
- The number of incumbent-incumbent links (yellow); and,
- The number of repeat incumbent-incumbent (red)

Consistent with the previous examples, we also catalogue and represent these relationships graphically to quickly summarize its nature and possible benefits. We demonstrate these graphs in Figure 3.38 and Figure 3.39.

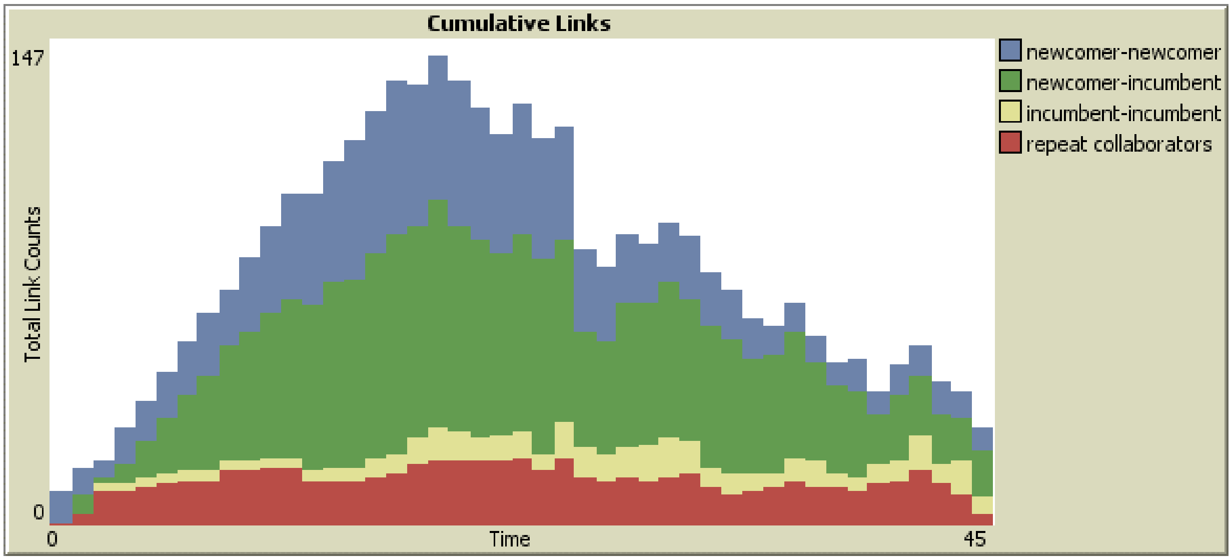


Figure 3.38 Visualizing Experience in a Collaboration. Visualizing the relative mixture of linkage experiential types between designers using a stacked histogram of link provides context into the overall nature of the collaboration. Using this plot, the analyst can surmise the relative experiential mix of the designers. In this instance, it is clear that over the course of the design, the collaboration favors an increasing proportion of newcomers early on its exploration while maintaining a relatively consistent basis of experiential expertise in the incumbent based linkages. This sort of data can allow for inspection as to the role having stability among certain experiential categories can play in the overall outcomes of a design effort. Specifically, many of the collaborations between incumbents, especially when repeated, represent a storehouse of institutional knowledge that provides stability to the design-team and its effort.

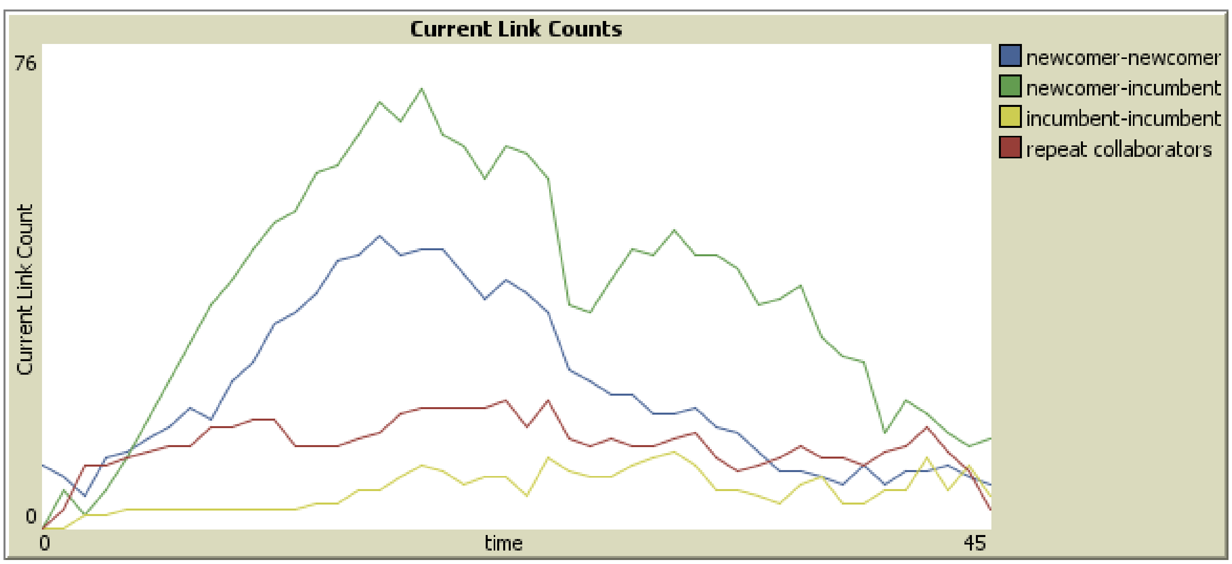


Figure 3.39 Visualizing the Current Count of Individual Link Types. This figure similarly provides the analyst insight into the relative skill mixture of the design collaboration. Here we use a line plot to allow the analyst to quickly detect when quantities of a certain collaboration dominant over another. For example, in this graph the analyst can quickly reference the point at which repeat collaborations between incumbents surpass newcomer-newcomer relationships. These intersections represent key phase transitions points in the makeup of a design. Future exploration along this line allows the analyst to derive the relative responsive of a collaboration to a given strategy or event.

In addition to the nature of the underlying individual collaborations, there are a number of other key characteristics when describing these collaborative design networks. We demonstrate these relationships graphically in Figures 3.36 - 3.38. These additional data include:

- The number of agents connected to the dominant (i.e. primary) collaboration;
- The number of agents that have splintered from the dominant collaboration;
- The number of overall design collaborators;
- The number of separated factions (i.e. components) from the dominant collaboration;
- The number of designers in each component;
- The separation distances between designers;
- The degree of clustering among agents; and, similarly,
- The degree of connectedness among agents

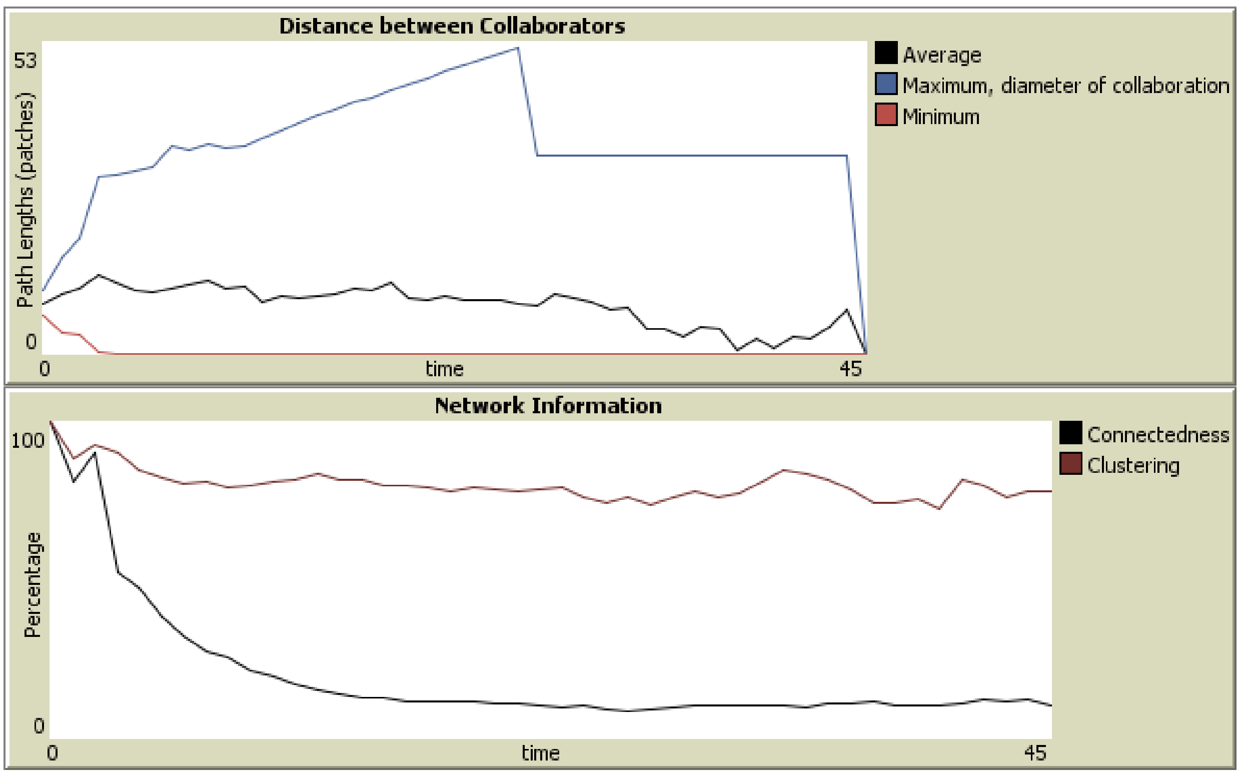


Figure 3.40 Graph of Network Statistics. The nature of the collaboration network, both in terms of the relative separation between agents and their connectivity, gives the analyst insight into how performance relates to various network characteristics, such as the formation of tight social cliques. The separation between agents, as measured by their path lengths, in the above figure provides insight into how diverse the thinking was of the DAU over time. The bottom figure provides insight into the relative connectedness (i.e. density) of the ADMUs to one another (i.e. current links relative to total possible number of links) and, on average, how tightly clustered agents are with their connections (i.e. number of closed triplets relative to the number of connected triplets of ADMUs).

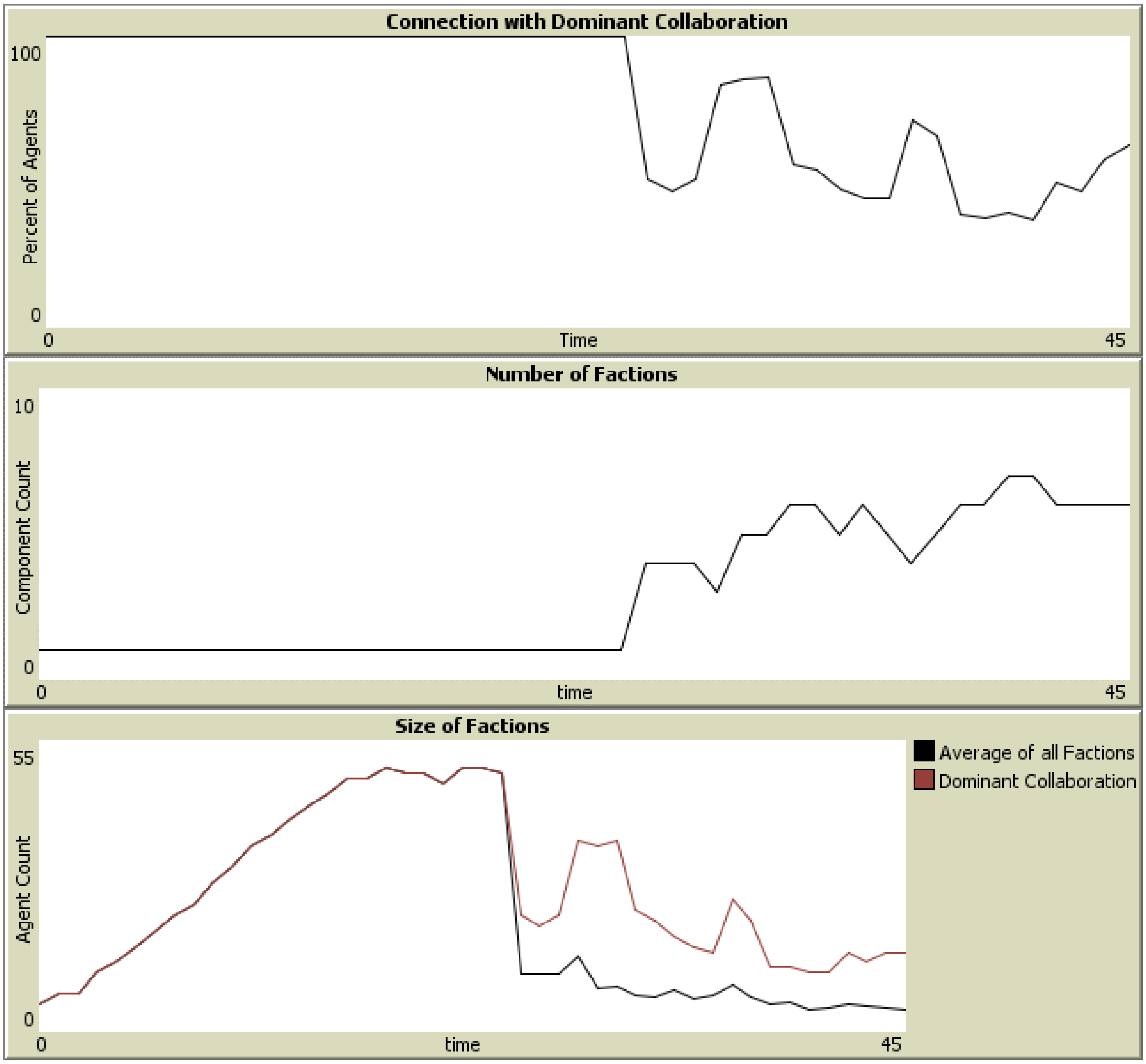


Figure 3.41 Network Size and Faction Graphs. The percentage of agents in the main (i.e. dominant) collaboration (top), the number of factions (i.e. components) present (middle), and the average size of factions (bottom) provides the analyst insight into developing strategies that match the relative nature of a collaboration, such as the degree of current fracturing in the collaboration. For instance, this percentage of designers participating in the dominant "giant component" may indicate to the analyst a need to reduce newcomers or to encourage repeat collaborations, depending on the objectives of the analyst. As part of Chapter 5, we examine how different values of design complexity K can influence the performance of the collaboration. Similarly, further analysis can relate these discussed network properties to the same considerations. The top graph provides an indicator as to how many of the designers belong to the giant component, a single connected component that contains the most of the nodes in the network. It can also provide insight, when combined with other information (e.g. connectedness), into the existence and characteristics of any factions. Sometimes these factions can grow into strongly connected cliques; cliques occur when every designer connects to every other designer in its component or faction. These parameters provide the C^{2}D model great flexibility in pursuing further explorations into network models and additional network dynamics outside of the existing hypotheses posed in Chapter 1.

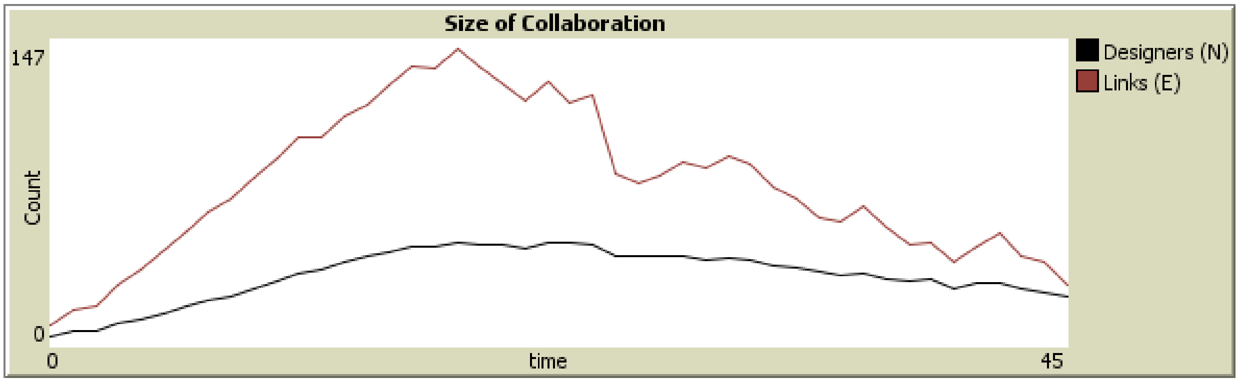


Figure 3.42 Overall Size of the Collaboration Graph. The overall size of the collaboration given by its number of nodes N (or in the case of C²D ADMU designer-agents) and the quantity of their interactions given by their links. These links range in quantity from a tree of $N - 1$ to its maximum number given by Metcalf's law, *i.e.* $N(N-1)/2$. These collaborations commonly reach a steady state, given enough time. Of theoretical interest, a key question for continued development is the existence of notional sustainability curves for the size of a collaboration based on the complexity of the design space.

3.5.1.4 Strategy Driven Dynamic Changes to Experimental Inputs

In the C²D model, strategies commonly utilize the percepts of the individual designers to guide their design behaviors. Specifically, strategies may dynamically change values for both diversity and management pressure over the course of the design process. We capture each of these values for each increment of time as follows:

- Current maximum allowable diversity; and,
- Current management pressure

We captures these values graphically, as shown in Figure 3.43.

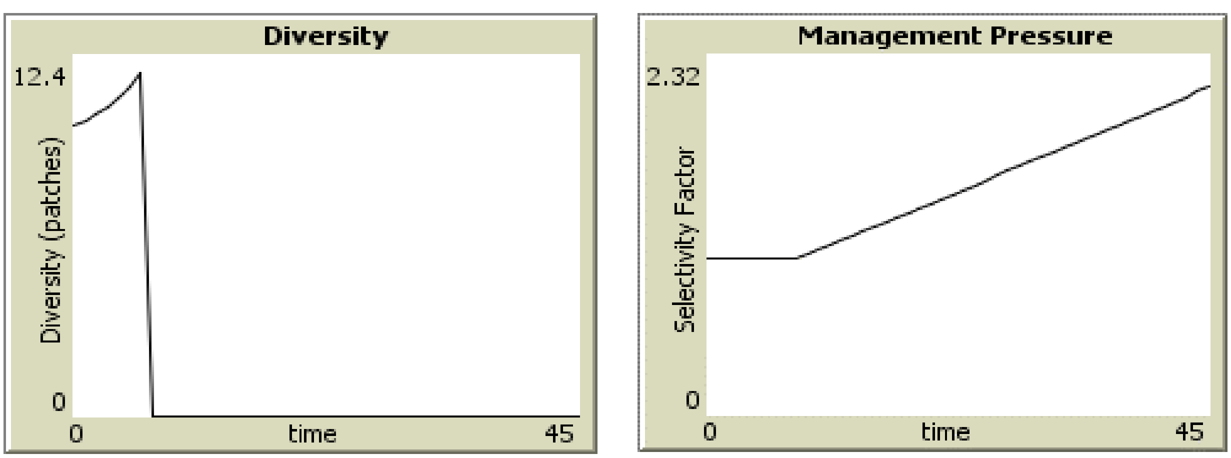


Figure 3.43 C²D Diversity Levels (left) and Management Pressure (right)

3.5.2 Expected Insights and Outcomes

As discussed in Chapter 2, engineering design tends towards the creation of increasingly complex artefacts. In other words, just as natural systems evolve to towards complexity, design builds upon its creations in a self-edifying process of discovery and continual improvement. From its earliest successes, engineering design has pushed the boundaries of human knowledge in the creation of new technologies and artefacts. However, these mounting complexities leave many current practitioners grappling with a central concern – has our approach toward design reached a fundamental limit in its continued progress? Can we, as designers, no longer design big things? The complex systems approach to engineering design provides an approach to explore these questions and, more importantly, a framework for studying strategies that may enable designers to meet the challenges posed by these questions. The generation of complexity-based strategies provide a powerful means for understanding and reinventing the design process.

As we have already discussed, the designer-artefact-user (DAU) system represents a complex adaptive system comprising physical, functional, cognitive, and socially constructed realities. By understanding and evaluating strategies from the perspective of these realities and their interactions within this system, design researchers may find ways to incentive beneficial patterns of behaviors. More specifically, we expect the development of insights into emergent behaviors that can improve design outcomes. We believe that in the long-term that this approach to design systems will enable design organizations to overcome the limitations imposed by an increasing degree of complexity.

In the near-term, within the scope of this current research, we expect the development of insights relevant to the design of systems. We expect the C^2D model to demonstrate and confirm the existence of beneficial patterns of activities for these designs relative to their varying complexities. For example, we suspect that early in the design process, based on initial observations derived from this research, the search among designers should remain aggressive in terms of both the size of the collaboration and the diversity of ideas it pursues. Additionally, we expect that the C^2D approach will similarly demonstrate that risk-taking, *e.g.* use of annealing or long jump strategies, behaviors can benefit a design collaboration early in the design process. The deliberate implementation of strategies over the course of the design cycle provides insights relevant to achieving improved design fitness and minimizing design times. Conversely, we expect that later in the design process conservative approaches toward design should being to dominate the search behaviors of the designers. The exploration of these concepts, as well as the hypotheses highlighted in Chapter 1, drive the analysis and design of experiments in Chapter 5 with the hopes of developing insights to improve the design process. We capture preliminary insights generated from the C^2D approach in Table 3.19 to highlight examples of the types of insights and outcomes expected from this research approach.

Table 3.19 Preliminary Design Strategy Inferences

	Less Collaborators	**More Collaborators**
Design phase	late	early
Design complexity K	small K (smooth landscape)	large K (rugged landscape)
Technology change rate	static landscape	dynamic landscape

	Less Diversity	**More Diversity**
Design phase	late	early
Design landscape K	small K (smooth landscape)	large K (rugged landscape)
Technology change rate	static landscape	dynamic landscape

	Less Risk-Taking	**More Risk-Taking**
Design phase	late	early
Design landscape K	small K (smooth landscape)	large K (rugged landscape)
Technology change rate	static landscape	dynamic landscape

4

C^2D Model and Formulation

"Remember that all models are wrong;
the practical question is how wrong do they have to be to not be useful."

Box, G. E. P., and Draper, N. R., (1987)
Empirical Model Building and Response Surfaces, John Wiley & Sons, New York, NY.

In the previous chapter, we provided the conceptual linkages associating complex adaptive systems (CAS) to engineering design through the designer-artifact-user (DAU) collaborative system and the construct of the design landscape. We provided a method to develop this landscape from the interacting or interdependent design elements. In the context of the DAU relationships, we demonstrated that the interactions between the designer, technology artifact, and the user form a complex adaptive system. From these initial conceptual linkages, we focused on the dynamics governing the formation of design-teams to focus the exploration. The discussed dynamics formed the basis for our exploration of design performance. We then proceeded to implement this framework in a model. The resulting model relates design complexity to the ruggedness of design landscape and incorporates the collaborative designer-artefact-user (DAU) system as a collaborative complex adaptive system (CAS) using agents-based decision making units (ADMUs). In particular, we implement the team-formation dynamics discussed in Chapter 2 to these ADMUs. By linking these two aspects into a singular model, we created a platform to evaluate the role of essential collaboration dynamics to that of design performance. We named this bridging methodology and model the *Complex Adaptive Performance Evaluation Method for Collaborative Design* (C^2D). Our discussion now moves to a detailed discussion surrounding this agent-based model (ABM) simulation and the details of its implementations as it pertains to this research. We have adopted the Holland (1999) constrained generating procedure (*cgp)* notation to help focus the discussion on the fundamental elements of the model. For illustrative purposes, we focus on the NetLogo v5.0.5 implementation of the model. NetLogo is an agent-based modelling platform developed by the Northwestern University Center for Connected Learning and Computer-Based Modeling (Wilensky 1999).

4.1 C²D Formalisms

A formalism provides the format for a pre-defined representation of knowledge or insight. We define formulations as the set of concept, their relationships, and their ontologies used to represent a set of accompanying rules specific to a particular task, *i.e.* to guide the externalization of knowledge (Suthers 2001). In the process of rationale design, formalisms provide an explicit representation of the reasons behind the decisions made in designing a system. For example in the Question, Options, and Criteria (QOC) model of design (used to explore design possibilities and at the heart of most design-trade processes), design problems are posed as questions and possible answers to these questions as options (MacLean, Young, and Bellotti 1991). We define these options, when linked with criteria (i.e. objectives), through measures of performance (i.e. fitness) using technical assessments. It is in this vein that formalism, especially in the case of QOC, represents a way to express the movements of design ADMUs as they search what we have deemed the design landscape. More broadly, the use of formalism allows us to express the C^2D model both with rationality and with enough commonality to reach the multiple and interrelated research communities connected to its content.

To represent our model we need to consider its contributions and construction. Our model integrates two primary facets, the DAU collaboration (implemented through model agents and their attributes) and a fitness landscape (implemented through the modelling environment) to describe the behaviors observed during the course of a design process. We model the DAU system as a composition of design agents searching a fitness landscape in order to develop insights into the relationships between complexity of design artefacts, collaboration dynamics, and the performance of design-teams. In short, our framework relates the design agents to the decision-makers, both designer and user, of design and the fitness landscape to aspects of the artefact. In order to implement this approach, we adopted the team dynamics most responsible for team performance as described by Guimerà, Uzzi, Spir, & Amaral (2005) and the NK fitness landscape model described by Kauffman (1993) as the basis for our design landscape. By applying these concepts to design we provide a novel way to inspect for complexity in the design process and, more importantly, a powerful way to relate this complexity back to the designer and user responsible for performing design tasks. We further build on these theoretical concepts in our model. One of these additions includes the possibility of dynamism on the design landscape.[40] We formalize the pertinent relationships and associative inferences made in the previous chapter through a series of procedures. These procedures allow for the precise communication of the approach and the model implementation. We first provide a conceptual overview of these procedures and then proceed to apply them to the C^2D model. It is the goal that these procedures can capture and relate the key concepts of our model as highlighted in Figure 4.1 and Figure 4.2.

DAU Environment

DAU Complex Adaptive *Socio-Technical* System

Emergence: State and Behavior

Collaboration Network: Structure and Organization

Agent DMU: State and Behavior

Agent (*micro*-) level - The smallest system entity or component in the C^2D model is that of the individual DAU collaborator and ADMU.

Network (*meso*-) level – The collaboration network captures the structure of interactions between the agents of the DAU.

System (*macro*-) level - DAU emergent properties appear from the individual agents, including their properties and their interactions through the collaboration network.

Figure 4.1 Framing the DAU and its Ontology for Discussion

[40] A dynamic fitness landscape is similar in concept to environmental-factors influencing the NK fitness landscape, such as discussed in the $E(N:K)$ model by Podlich and Cooper (1998). In this context, we allow for the possibility of deformation and continual change to the design possibilities space. This corresponds, conceptually, to changes in the accessibility of new or existing technologies. In the context of Data Envelopment Analysis, this also provides an analogy to the shifting of the efficient frontier. Within the existing model, we can implement this change through a user defined stochastic technology change rate equation.

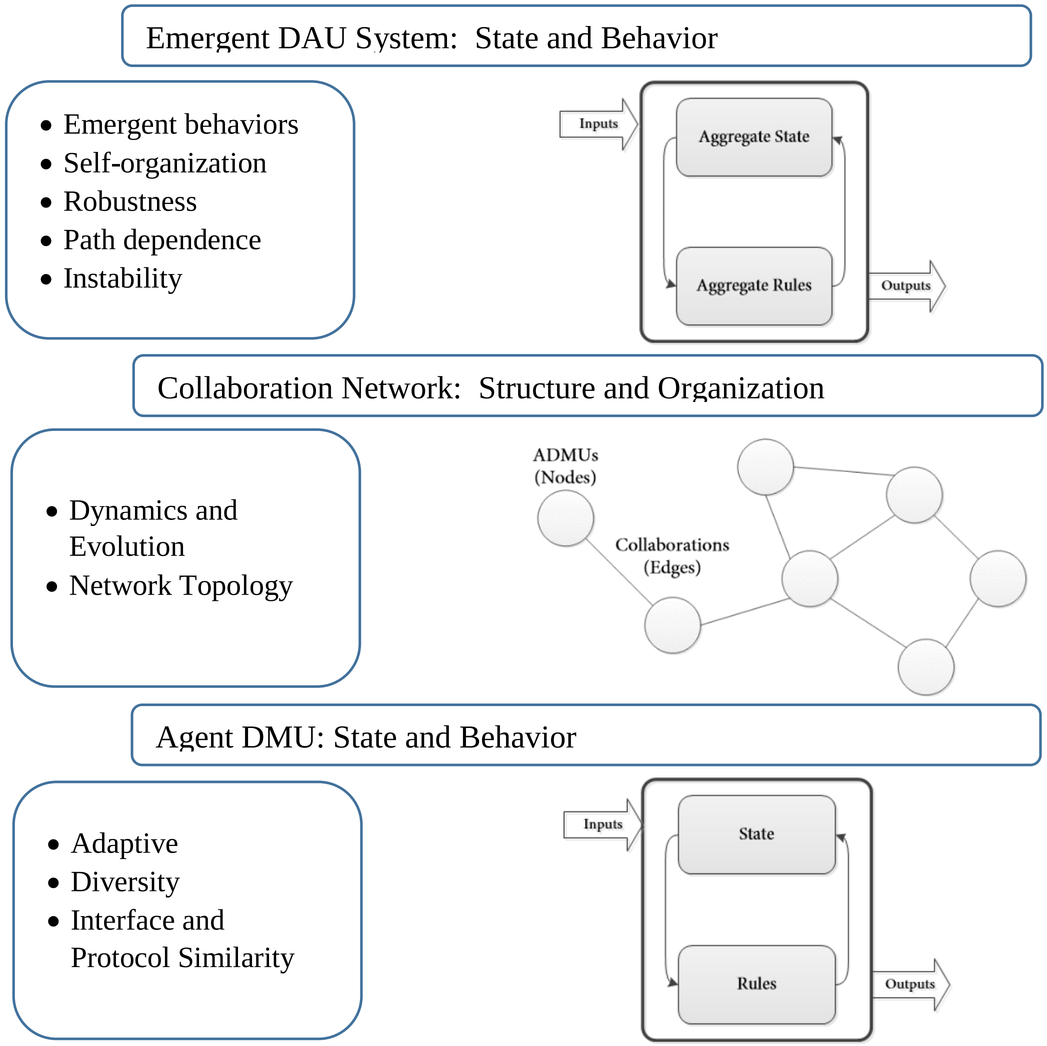


Figure 4.2 Characteristics of the DMU Framework

4.1.1 Constrained Generated Procedures

Holland (1999) provides a useful and logical structuring for notating these relationships and their implementation in the C^{2}D framework using constraint generating procedures (*cgp's*). Holland (1999) explains that the dynamic nature of agent-based modelling requires a procedure based approach to describe modelled systems with sufficient conciseness. Agent-based modelling uses a bottom-up perspective of systems. In this context, these rules describe how individual agents act and react to each other, following their internal rules. The overall system behavior emerges out of these interactions. In our model, the individual agents interact through their collaborations in the DAU. We adopt this *cgp* notation, as described in this section, to communicate our model of the DAU in the following section. This notation will also allow us to communicate the dynamics, at the necessary level of granularity, driving the relationships in the simulated data discussed in the concluding chapters of this work. Dougherty, Triantis, Ambler (2014) followed a similar approach for describing and specifying their modelling approach for a similar performance measurement agent-based model (ABM), the Complex Adaptive Performance Efficiency Method (CAPEM) model. The CAPEM model applied the well-used flocking metaphor seen in the behavior of birds to economic units (i.e. decision-making units); similarly, C^2D represents the DAU as a CAS system through the adaptations of design agents (i.e. decision-making units) on a design landscape. This representation allows us to examine the complexity of the technosphere and its relationship to engineering design through the design possibility space bounded by the design landscape, as well as the behaviors of the design teams and their collaborative team formation dynamics. As a design team navigates a design landscape, the team must converge towards increasingly fit designs. The use of *cgp's* allow us to clearly understand the mechanism and functions that drive the model, such as the designers finding fitness. We can also think of these procedures also responsible for generating these fitness values. Mathematically the design landscape provides a value feature v that assigns all possible states S (i.e. configurations of design-team locations on the landscape) to a real valued (f_d^*) fitness score for design. In this sense, we can think of this value feature as a function of the *cgp's* and in the case of C^2D a fitness component (i.e. design parameter). This particular function is similar to the weighted value feature described by Holland (1999), based on Samuel (1967), for a board at state $s \in S$ in the following equations:

$$v\colon\ S \rightarrow f^* \tag{4.1}$$

$$V(s) = \sum_i w_i\, v_i(s) \tag{4.2}$$

Where:

v_i: inputs to valuation function, $i = 1 \ldots k$

w_i, weight applied to the ith feature

In its application by Samuel (1967), $v_i(s)$ provides, as explained by Holland (1999), an input to a pattern recognition procedure. In this particular example, the input corresponds to the presence or absence of a signal, *i.e.* a synaptic pulse, and results in a binary choice for each input i, which in this case corresponds to synapses. In short, $v_i(s)$ takes a value of one (in the presence of a pulse) or zero (in the absence of a pulse) for each synapse i. Similarly, the weighting w_i in the example represents the efficiency of the synapse i in performing its function. The relation of the efficiency and presence of a synapse gives rise to the overall valuation formulation employed by Samuel (1967) as seen in the above equation (4.2). The C^2D model and framework discussed in Chapter 3 similarly considers $v_i(s)$ as inputs into the creation of fitness landscape, which correspond in theory to the value functions as described by Collopy (2011) and remains equivalent to a modification of equation (2.16) discussed in Chapter 2 describing fitness. Although C^2D allows for the creation of landscapes directly from these value functions, we focus primarily on procedurally derived and stochastically generated fitness values as discussed in Section 3.2.2 of Chapter 3 in order to explore the role of complexity in engineering design performance. In this approach, these fitness values, as in the case of the example from Samuel (1967), depend on a binary relationship, which in our case corresponds to the presence or absence of a relationship between a functional requirement and a design parameter. We equate in our approach the number of functional requirements to N and the number of interactions between functional requirements to design parameters as K following from the Kauffman (1993) NK model. As a result, the expected values and statistical relationships for the resulting fitness values in C^2D follow from the NK findings from Kauffman (1993) and Altenberg (1997).

This valuation premise, according to Holland (1999), forms the foundation of creating adaptive strategies. The macro-strategy for the C^2D model centers on the goal of incentivizing efficient and effective movements across a potentially rugged design space in an effort satisfice design requirements, *i.e.* deliver value, in the least amount of time. In terms of the model and *cgp's*, a strategy simply means a procedure to determine the unique movement of the designers as they explore the design space, and an adaptive strategy simply differentiates itself through as it more particularly refers to the decision-maker's ability to understand its performance relative to the past and make changes to these procedures. These procedures consist of mechanisms, which drive the fundamental dynamics of a system, and a set of allowed interactions between the mechanisms, which constrain the possibilities in a way similar to the rules of a game limiting the possible configurations of a board.

The *cgp's* themselves represent a broad set of hierarchical models. These models (e.g. agent types, agent environments, simulation interfaces) capture the dynamics of a set of component mechanisms and their underlying allowed interactions. These underlying interactions both enable and constrain these mechanisms. More formally, c*gp's* (C) are comprised of mechanisms (F) (e.g. agent goals, rules, percepts, actions) that are similarly comprised of sub-mechanisms (f) (e.g. subordinate variables, parameters, reporting functions, display functions) in strict hierarchies. Mechanism and sub-mechanisms provide transformation functions, providing cause and effect relations between the inputs and the states of the mechanism. Holland (1999) provides a set of guidelines for establishing these procedures:

1. Define the *mechanisms* that govern the simulation (e.g. rules, laws). These *mechanisms* represent the transformative devices for converting process inputs, actions, and information into outputs, *i.e. mechanisms* describe the black box of production systems discussed in Chapter 1. When linked together these *mechanisms* form *networks*, which often span multiple types of *mechanisms*. The complexity central to Holland's work (1999) originates from these *networks* (i.e. the interaction of *mechanisms*); these interactions result in the organized and unanticipated patterns of behaviors central to the Holland (1999) interpretation of *emergence*. These *networks* can remain fixed, constraining the mechanisms to a fixed landscape, or dynamic. In the C^2D model, like other dynamic or transitional systems, DAU agent based decision-making units (ADMUs) of the model create and dissolve linkages, creating a constantly evolving and dynamic network of collaboration. These DAU ADMUs operate on either a static or dynamic design landscape depending on the particular configuration of the simulation.
2. Define the *state* of the interlinked mechanisms in terms of their *component mechanisms*.
3. Describe the *transition function* that allows for future state changes constrained by the set of possible interactions of the *component mechanisms*.
4. Establish the system *hierarchy* by using basic *mechanisms* as subassemblies for building increasingly more complex *mechanisms* (i.e. each *cgp* acts as a *mechanism* to build more complex *cgp's).* Holland (1998) equates this *hierarchy* to the central driving force behind emergence, as seen in the complex and hierarchical relationships between the molecule, organelle, cell, organ, and organism in biology.

Ultimately, Holland (1999) credits the precision of the *cgp* notation as an essential contributing factor in detecting and differentiating any emergent behaviors from non-emergent behaviors.

Table 4.1 Constrained Generating Procedure for the C²D Simulation, $n(C) = 6$

Cgp ($\boldsymbol{C}$)	Description
C_{SIM} = (C_{ENV}, C_{LND}, C_{INT}, C_{COL}, C_{ADMUs}, C_{STR})	The simulation is a strictly closed system constrained by the cgp (C_{SIM}). This system represents a composite procedure that encompasses lower level procedures to control the agent environment, the design-landscape, the user interface, the team-formation and collaboration dynamics, and the population of DAU agents and their characteristic search strategies.

Using this notation, the C^{2}D CAS ABM simulation (C_{SIM}) is composed of a set of *cgp's*. These include the simulation interface (C_{INT}), the agent environment (C_{ENV}), the population of CAS ABM agents representing the DMU agent based decision-making units and its strategies (C_{ADMUs}), the design landscape (C_{LND}), the driving collaboration dynamics (C_{COL}), and the search strategies employed by the DAU system (C_{STR}). These initial categories of *cgp's* remain arbitrary, but serve to capture the complete hierarchies required to describe the C^{2}D model. As we proceed to Section 4.2, we will provide descriptive notation for each of these *cgp's* as a way to describe the implementation of the model concisely. For the remainder of this section we expand on the construction of these *cgp's* and their characteristics as described by Holland (1999).

4.1.1.1 Combining and Interfacing Constrained Generating Procedures

A small set of rules govern the combination of *cgp's*, whose combinations form increasingly complex *cgp's* that lead to the accretion of the overall model. We summarize these rules as follow:

1. A *cgp* can be made up of one or more mechanisms (F), which themselves can be made up of one or more sub-mechanisms (f);
2. Adding a new mechanism or sub-mechanism to an existing *cgp* creates a new *cgp* (C');
3. Existing *cgp's* $(C \text{ } and \text{ } C')$ can be connected forming a new *cgp* (C'');
4. All *cgp*'s (C) are formed via combinations of existing *cgp's*; and,
5. *Cgp's* (C), mechanisms (F), and component mechanisms (f) must allow for unique identifiers, index numbers.

These rules mathematically establish all *cgp's* as a combination of assemblies such that $C = \{F_1, F_2, \dots, F_n\}$ and $F = \{f_1, f_2, \dots, f_m\}$. We include this discussion for completeness while demonstrating the flexibility of the hierarchical notation schema. Each of the mechanisms F and sub-mechanisms f in this approach require a set of input I and state S variables. These input variables I represents a set of possible inputs $\{I_1, I_2, \dots I_k\}$. This resulting input I also represents the product of all possible input sets such that if $I_1 = \{a, b\}$ and $I_2 = \{c\}$ then $I = I_1\ x\ I_2 = \{(a, c), (b, c)\}$. Similarly, the state S represents the set of possible states $\{s_1, s_2, \dots s_h\}$. In this structuring, the mechanism (F) or its sub-mechanism (f) provides the transformation function for these inputs and state variables (both current and future), *i.e.* $f: I\ x\ S \rightarrow S$, or, using expanded notation $f: \{I_1, I_2, \dots I_k\}\ x\ S \rightarrow S$. To capture this dynamic at any point in time requires expressing this relationship as $S(t+1) = f\big(I_1(t), I_2(t), \dots, I_k(t), S(t)\big)$. Further when constructing overall *cgp's, e*ach of these transition functions f represent a unique combination of inputs and set of possible states. Modifying the preceding formulations allows for the representation of these multiple mechanisms as $f_h: I_h\ x\ S_h$ where, similar to above, $I_h = I_{h1} x\ I_{h2} x \dots x\ I_{hk(h)}$ designates the possible inputs to sub-mechanism h where $k(h)$ provides the total number of inputs to sub-mechanism h. After having related all of these sub-mechanisms to their inputs and their possible states, it is then necessary to relate these entities to their primary mechanisms F. These relationships provide the scaffolding to describe the C^{2}D model, and more generally a method to explore and capture the transformative processes of any production system through further development of this notation.

Holland (1999) goes beyond our immediate purposes to provide this development. In particular, Holland (1999) provides the linkages between mechanisms F using a single state set $S = S_1 \cup \dots \cup S_m$. This single set links all m possible state sets through their union. Because this union includes multiple associated state sets and varying inputs, an interface function $g_{ij}: S \rightarrow I_{ij}$ provides the necessary relationship linking an input j to its mechanism i. As a result, mechanism h relates to input j according to the relationship $I_{ij}(t) = g_{ij}\big(S_h(t)\big)$ for all times t. This interface function g_{ij} applies to domains with a fixed geometry, that is, a set of mechanisms where the interface can be predefined and does not change throughout the simulation. For purposes of the C^{2}D scenarios discussed, the primary relationships and strategies (e.g. relevant to team-formation dynamics) relating inputs and states for a given mechanism also remain constant.

Ultimately, these composite mechanisms contribute to a composite *cgp* (C), consisting of n mechanisms. For concreteness, the C^{2}D model represents as composite *cgp* (C), consisting of multiple *cgp's* as described previously in Table 4.1. To formalize the relationships for this overall *cgp* (C) for C^{2}D we must also similarly capture the transition function f_C of the composite mechanism C, which similarly requires defining the inputs I and states S_c of this composite mechanism C. This resulting overall global state set of the *cgp* C is the set product (n-tuples) of the state sets of the individual mechanisms such that $S_c = \prod_i^n S_i$. However, addressing inputs I involves slightly more difficulty as these inputs for the composite mechanism C requires additional indexing to detail whether inputs connect ($H_{x,conn}$) to other mechanisms F or if they remain independent or free ($H_{x,free}$) from these other mechanisms F. Holland (1999) establishes the best practice of realigning indices so that all inputs in $H_{x,free}$ occupy the lowest portion of the index H_x. Similar to the earlier construction, the inputs $I_{x,free}$ from outside of the composite mechanism C follows, when using the suggested schema from Holland (1999), from the relationship $I_{x,free} = \prod_i^{k(x)} I_i$ where $k(x)$ is the total number of inputs of the mechanism type $H_{x,free}$. Alternatively, the values that an input I can provide to composite mechanism C always follows $I_C = \prod_i^n I_{i,free}$. Because the inputs $I_{x,conn}$ associated with $H_{x,conn}$ depend on other mechanisms in C, a function relating the global state to $I_{x,conn}$ also remain necessary for completeness. This relationship between $I_{x,conn}$ and the global state $g_x\colon\ S_c \rightarrow\ I_{x,conn}$ allows the determination of values for $I_{x,conn}$ for all time t through $I_{x,conn}(t) = g_x(S_C(t))$. This resulting transition function for the mechanism $f_x\colon\ I_{x,free}\ x\ I_{x,conn}\ x\ S_x \rightarrow\ S_x$ when restated, in terms of the component, follows $f_x'\colon\ I_{x,free}\ x\ S_C \rightarrow\ S_C$. For given values of $I_{x,free}, S_x$ and, S_C, f_x results in the same value as f_x' by definition allowing for a global transition function and complete composite macro-mechanism to capture all system dynamic behavior from Holland (1999):

$$f_C\colon\ I_C\ x\ S_C \rightarrow\ S_C \tag{4.3}$$

$$S_C(t+1) = f_C\big(I_C(t), S_C(t)\big) = [f_1'\left(I_{1,free}(t), S_C(t)\right), \ldots, f_n'\left(I_{n,free}(t), S_C(t)\right)] \tag{4.4}$$

Precisely defining and indexing these *cgp's*, mechanisms and component mechanisms as inputs and states and using these standardized descriptors enables researchers to "completely determine the dynamic behavior of the composite macro-mechanism" and the essential tools necessary for discovering and understanding emergence in complex adaptive systems (Holland 1999). We take advantage of the indexing schema provided by this approach in the following section to outline the model through a set of standardized descriptors as described below. We provide the previous discussion to highlight the tractability of identifying and tracing model behaviors to constituent inputs and the underlying mechanisms. It is the goal that the continued maturation of this approach will allow continued research to identify sources of emergent DAU behaviors beneficial to design.

4.1.1.2 Standardized Descriptors

To capture each mechanism and each sub-mechanism (along the lines of the goals discussed) we implement a generic notation schema to provide a standardized descriptor for this research. This descriptor format adheres to the *cgp* rules and relationships described above. This standardized descriptor provides the structure with which we enumerate the necessary inputs and includes a unique identifier for both the descriptor itself and for the transformation function involved. Table 4.2 provides the generic format for this descriptor.

Table 4.2 Generic Standardized Descriptor Format for Mechanisms and Sub-Mechanisms

Unique binary identifier for the *Cgp*	Unique binary identifier for the transfer function (mechanism or sub-mechanism) being employed	Inputs 1 …n (including sub-mechanisms for mechanisms)	The internal state of the transformation function used by this mechanism or sub-mechanism

This structure becomes useful in assembling a complete list of standardized descriptors for all components (mechanisms and sub-mechanisms) which form a "current component list (ccl)" or, given fully specified states, a "current state list (csl). Holland (1999) affirms the usefulness of this notation when sufficiently precise and robust in forming a general computing machine, and advocates for its use a common language for the complex adaptive systems (CAS) agent-based modelling (ABM) community. Moreover, Holland (1999) advocates for the use of these computing machines in massively parallel processing environments to trace precise agent behaviors and increase the likelihood of differentiating expected behaviors, computable behaviors, and emergent behaviors. By assembling a complete list of standardized descriptors for all components (mechanisms and sub-mechanisms) of a simulation, we can better understand system behavior.

An indexed set of *cgp's*, mechanisms, and sub-mechanisms described entirely by their inputs and their states have been used by Conway (1970) to fully specify and construct a simulation of "Life" in which a community of patterns emerge from simple models of cellular automatons. These patterns emerge from the interaction and evolution of these automatons on a checkerboard-like configuration made up of just eight inputs and two states (Holland 1999). Examples of the application of this structure also follows from Holland (1999) who used it to fully specify and construct a simulation called "Echoing Emergence" or Echo in which he demonstrates the capabilities of genetic algorithms. This notation successfully represented behaviors that replicate, combine, mutate and evolve an initial seed resource mechanism into a "well-formed complex aggregate" organism. Use of cellular automata and genetic algorithms remain outside the scope of this research but have proven the applicability of the approach. We assume that this notation provides the same ability to trace behaviors in engineering design systems, like the DAU. The mechanisms and component mechanisms of this approach easily lend themselves to describing and representing the associative inferences between the building blocks of the DAU CAS ABM and performance.

4.2 C²D Implementation: Operationalizing the DAU

We now focus on the describing the C^2D key *constrained generating procedures (cgp's)* and their constituent elements: the modelling environment, the design landscape, the user interface, the collaboration dynamics, the DAU ADMUs, and the design strategies available to the DAU. We choose this representation as it aligns to a set of natural divisions within the simulation and provide easily differentiable constructs within the model. We refer the author for completeness to the C^2D GitHub library for the model source code (cf. https://github.com/nambler/C2D) or from its GitHub page (cf. http://nambler.github.io/C2D/). Each of the following sections will include a discussion of the mechanisms and sub-mechanisms of the C^2D model. In the development of the C^2D model discussed, we have adapted conceptual mechanisms from the David McAvity model of evolutionary mechanics (2006) and the Baskhy and Wilensky (2007) team assembly model as described in Chapter 2. In the context of the DAU as a productive system, we implement the design possibility space as the CAS ABM environment vis-à-vis the modelling environment, we introduce the concept of a bounded design possibility space through the construction of a design landscape, and we implement the DAU through a set of CAS ABM agents. We use inter-agent linkages to represent the interactions among these designers that give rise to their network characteristics. In short, our framework relates the design agents to the decision-makers, both designer and user, of design and the fitness landscape to aspects of the artefact.

As described by Cooper, Seiford, and Tone (2007), the production possibility space (PPS) is a key property of any production system. As part of Chapter 2, we compared the DAU system to a general production system using insights from Triantis (2012) and Dougherty, Ambler, Triantis (2014). For implementation purposes, we now compare this PPS to the construction of an agent environment for the DAU. We implement the concept of the DAU and the design PPS through the mechanisms and sub-mechanisms for C_{ENV} shown in Table 4.3 and the mechanisms and sub-mechanisms discussed subsequently for C_{LND} in Section 4.2.2. We utilize the native capabilities of our modelling platform, NetLogo, in the description of our modelling environment. Like the PPS, we must define the modelling environment (W) with sufficient real valued size to encompass or represent all feasible combinations of inputs (i.e. functional requirements and design parameters) and outputs (i.e. fitness). The two dimensional, positive, semi-definite (i.e. $f(0) = 0$ *and* $f(x) \geq 0$ for every non-zero $x \in W$) coordinate space in the C^2D implementation (with an origin at zero) ensures that all combinations are real valued combinations of inputs and outputs. In *cgp* notation, the W given by C_{ENV} comprises mechanisms that scales the space and time, and defines the origin, boundaries, and topology of the space.

Table 4.3 Elements of the *Cgp* Composing the Agent Environment, C_{ENV}

***Cgp* & Mechanism**	**Description**
$C_{ENV} = \sum_{i=1}^{n} \sum_{j=1}^{m} F_{ENV_{ij}}$	The agent environment is composed of the key functions shown below (** implies it is natively assigned by the NetLogo software*):
$F_{ENV_{01}}$	Define Units of Space (Patches)*
$f_{ENV_{0101}}$	Set patch size (pixels)
$F_{ENV_{02}}$	Define Units of Time (Ticks)*
$F_{ENV_{03}}$	Establish Location of Origin*
$F_{ENV_{04}}$	Establish Boundaries of Space
$f_{ENV_{0401}}$	Set minimum x-coordinate (patches)
$f_{ENV_{0402}}$	Set maximum x-coordinate (patches)
$f_{ENV_{0403}}$	Set minimum y-coordinate (patches)
$f_{ENV_{0404}}$	Set maximum y-coordinate (patches)
$F_{ENV_{05}}$	Establish World Topology *(Torus, Box, Vertical Cylinder, or Horizontal Cylinder)*
$f_{ENV_{0501}}$	Set horizontal wrap
$f_{ENV_{0502}}$	Set vertical wrap

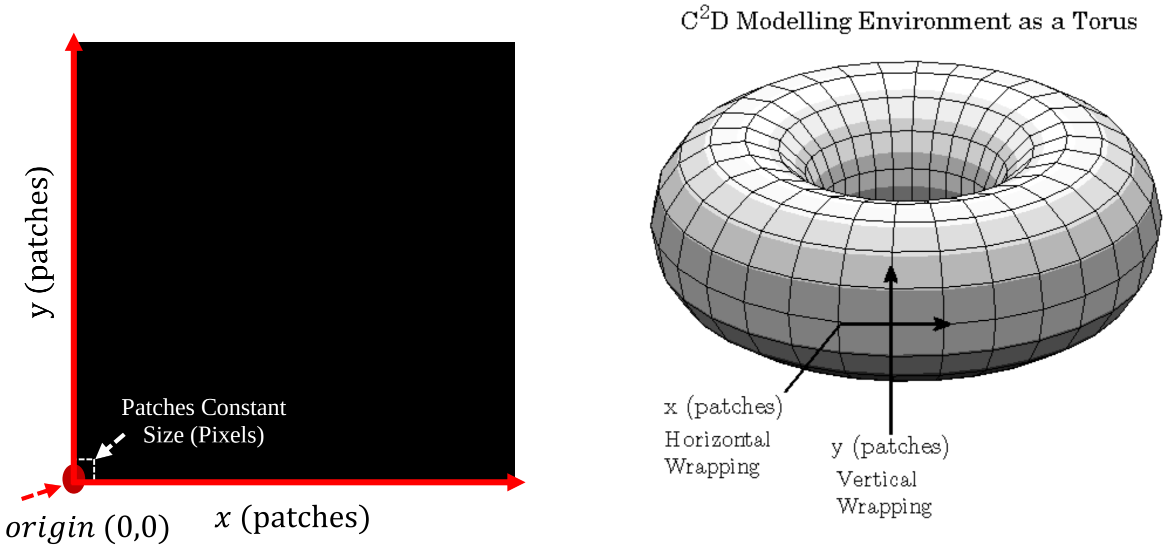


Figure 4.3 C²D Modelling Environment Enabled through NetLogo

Although we have constructed both a 3-dimensional C^{2}D model as well as a gradient model for representing fitness, we focus in this chapter on the gradient model used later for experimentation in Chapter 5. In the experimental runs, we keep all aspects of the modelling agent environment constant. In other words, we define space in terms of patches and time in terms of ticks. We establish the C^{2}D coordinate system using the native NetLogo default origin of the lower left corner of the world display (0, 0). We then enable world wrapping for the axes (i.e. a continuous dimension of functional requirements in the conceptual context of C^{2}D) seen in Figure 4.3. This continuous wrapping ensures that all ADMUs see the entire world around it, as opposed to the topology of a cylinder or box world that has edges. Further, this wrapping allows the ADMUs to move freely from the right side or left side of the two-dimensional world to the left side or right side respectively, and, similarly, from the bottom or from the top to the top or to the bottom. For consistency throughout the runs, we define the maximum x-coordinate and maximum y-coordinate as 100 and define the minimum x-coordinate and the minimum y-coordinate as zero. Similarly, we maintain a constant patch size of 4.05 pixels. We establish these definable values at the beginning of each run using NetLogo native code (Wilensky 1999). The NetLogo commands for these mechanisms follows from the following code:

```
resize-world ( 0 ) ( 100 ) ( 0 ) ( 100 )    ;; (x min, x max, y min, y max)

set-patch-size ( 4.05 )   ;; sets the patch size in terms of pixels
```

Table 4.4 Descriptor for Establishing World Boundaries, $\mathrm{F}_{\mathrm{ENV}_{04}}$

Unique Binary for *Cgp*	Unique Binary Identifier for the Transformation Function Involved	Input 1 (0001)	Input 2 (0010)	Input 3 (0011)	Input 4 (0100)
0001	0100	max-pxcor	min-pxcor	max-pycor	min-pycor
$\mathrm{F}_{\mathrm{ENV}_{04}}$		State Description			
		State of the transformation function described below.			

We can represent these mechanisms through standard descriptors. Table 4.4 highlights the primary input required from the C^2D model, the boundaries of the model environment. We use the standard values described above to enforce the boundaries of the model world. The state of the system starts with the world defaults of the NetLogo platform, after executing the *cgp* above we arrive at the settings for the C^2D world and modelling environment. We then assign fitness value to this world using the landscape *cgp*. We scale the design landscapes described to this established world.

4.2.2 C²D SIMULATION DESIGN LANDSCAPE

Aside for a design possibility space, we more particularly consider the DAU as operating on a theoretical landscape whose surface bounds all levels of possible fitness for a given design approach, similar to the role of the theoretical efficiency frontier in Data Envelopment Analysis. We view this surface as representing the most efficient allocation of design margins between the functional requirements and design parameters of a system. We use the NK concept from Kauffman (1999) as the primary mechanism in the creation of this design landscape, but also allow for user-defined fitness functions. The role of the landscape *cgp* ($\mathrm{C}_{\mathrm{LND}}$) centers on assigning real valued fitness values for each patch on the world. We outline this procedure in Table 4.5.

Table 4.5 Elements of the *Cgp* Composing the Agent Environment, $\mathrm{C}_{\mathrm{ENV}}$

***Cgp* & Mechanism**	**Description**
$\mathrm{C}_{\mathrm{LND}} = \sum_{i=1}^{n} \sum_{j=1}^{m} \mathrm{F}_{\mathrm{LND}_{ij}}$	The design landscape is composed of the key functions shown below:
$\mathrm{F}_{\mathrm{LND}_{01}}$	User-Defined Value Function, *i.e.* $f = A(xcor^{\beta})(ycor^{\alpha})$
$\mathrm{f}_{\mathrm{LND}_{0101}}$	Retrieve parameter A (i.e. total production factor)
$\mathrm{f}_{\mathrm{LND}_{0102}}$	Retrieve parameter β (i.e. weight for x-coordinate)

Table 4.5 Elements of the *Cgp* Composing the Agent Environment, C_{ENV} (Continued)

$f_{LND_{0103}}$	Retrieve parameter α (i.e. weight for y-coordinate)
$f_{LND_{0104}}$	Retrieve On or Off Status for User-Defined Value Function
$F_{LND_{02}}$	User-Defined NK Values for Stochastic Fitness Assignment
$f_{LND_{0201}}$	Retrieve value for N (number of functional requirements)
$f_{LND_{0202}}$	Retrieve value for K (number of interdependencies)
$f_{LND_{0203}}$	Calculate and report equivalent landscape smoothness S^*
$f_{LND_{0204}}$	Assign fitness values to landscape for NK
$f_{LND_{0205}}$	Retrieve On or Off Status for NK Value Function
$F_{LND_{03}}$	User-Defined Smoothness S^* for Stochastic Fitness Assignment
$f_{LND_{0201}}$	Retrieve landscape smoothness S^*(meta-parameter for NK)
$f_{LND_{0202}}$	Calculate and report equivalent value for K
$f_{LND_{0203}}$	Calculate and report equivalent value for N
$f_{LND_{0204}}$	Assign fitness values to landscape for NK
$f_{LND_{0205}}$	Retrieve On or Off Status for Smoothness S^*Value Function
$F_{LND_{04}}$	Shade Landscape According to Generated Fitness Values
$F_{LND_{05}}$	Error Messaging and Exception Handling
$f_{LND_{0501}}$	Count and report number of active landscape mechanisms

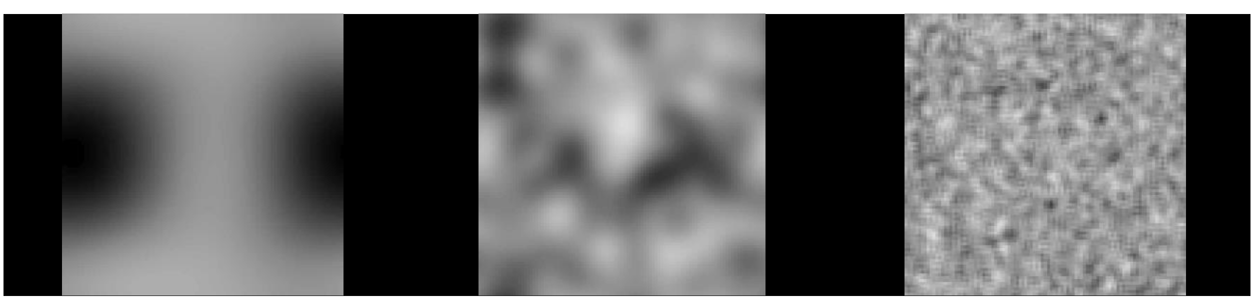
In the following chapter, we use both user-defined values of N (the number of functional requirements) and K (the number of interdependencies between requirements), as well as user-defined values for the smoothness, for testing the hypotheses established earlier from Chapter 1. As we have defined complexity as a measure of the density of optima, we use its converse the smoothness of a landscape in our general modelling. We can represent these mechanisms through standard descriptors such as those in Table 4.6. In the event that more than one approach is set "On" the error exception of $F_{LND_{05}}$ switches any conflicting commands to off.

Table 4.6 Descriptor for Establishing Using Smoothness to Assign NK Fitness Values, $F_{LND_{03}}$

Unique Binary for *Cgp*	Unique Binary Identifier for the Transformation Function Involved	Input 1 (0001)	Input 2 (0010)	State Description
0010	0011	S^*	On/Off Switch Status	State of the transformation function described below.
$F_{LND_{03}}$				

The described procedure takes user defined inputs for smoothness and assigns fitness values to the landscape. Since the construction of the landscape occurs in one of the three methods (i.e. $\mathrm{F}_{\mathrm{LND}_{01}}$, $\mathrm{F}_{\mathrm{LND}_{02}}$, $\mathrm{F}_{\mathrm{LND}_{03}}$) the procedure is also only activated when switched on (i.e. $\mathrm{f}_{\mathrm{LND}_{0205}}$) by the user using the interface *cgp*. The $\mathrm{F}_{\mathrm{LND}_{03}}$ mechanism works by first taking the user-specified value for smoothness $S^*$and then calculating an equivalent value for the parameter K. Values for N are similarly derived from the world dimensions. After arriving at these values, the code approximates a NK landscape by using the equation for the expected value for the number of optima and its variance to select an initial quantity and an initial random placement of local optima. The model then uses the smoothness factor to average its fitness (i.e. diffuse fitness command in NetLogo) repeatedly based on the smoothness factor. It then rescales the fitness landscapes to fitness tables from Kauffman (1993). We use this approximating technique to increase the speed at which NetLogo can generate these landscapes. The core coding elements for this mechanism as implemented in NetLogo follows:

```
to setup-patches-and-allocate-fitness
    …
    If use_smoothness_factor? ;; ID - 00100011
    [
    [ ifelse N > 1  ;; default (if coordinate max remain 100 and min remain 0) is N = 13.32
                    ;; N = log2 (count patches, 100x100 ) ~= 13.32 in default
    [ set K precision ( ( (smoothness - 100) * (N - 1) )/ ( 100 ) ) 2 ] ;; cf. equation (3.10)
    [ set smoothness 100 set K 0 ] ] ;; recall max K is N – 1
    [ ask patches [ set fitness random_NK_fitness_values ] ]
    repeat ( smoothness ) [ repeat fitness 1 ]
    rescale_to_NK_tables ;; scales optima to NK values from Kauffman
    vary_fitness ;; adds expected NK variance back into values
    color-landscape ;; applies color gradient for fitness values between 0 and 1
    ]
```



$S^* = 1$ $S^* = 0.5$ $S^* = 0$

Figure 4.4 Approximated NK Landscape for C²D using $\mathrm{F}_{\mathrm{LND}_{03}}$

As mentioned in the previous section, analysts must provide parameter values when using C^2D. We enable the analyst to input values into the C^2D model through a NetLogo user interface. We create this user interface (UI) by adding buttons, switches, sliders, and numerical inputs for the user within the NetLogo interface screen. The values for these inputs first load according to their defaulted values or states. When the analyst modifies these defaults, the simulation temporarily stores the new values or registers the command, making these values and commands accessible to all of the other *cgp's*. These values allow the analyst to define the landscape described in the preceding sections, as well as define the aspect of the DAU and its collaboration discussed in the coming sections. We outline the user interface through an associated *cgp* in Table 4.7.

Table 4.7 Elements of the *Cgp* Composing the C^2D Interface, C_{INT}

***Cgp* & Mechanism**	**Description**
$\mathrm{C_{INT}} = \sum_{i=1}^{n} \sum_{j=1}^{m} \mathrm{F_{INT}}_{ij}$	The user interface (UI) is composed of the key functions shown below (these functions temporarily store inputs values or commands):
$\mathrm{F_{INT}}_{01}$	UI for Model Actions and Commands
$\mathrm{f_{INT}}_{0101}$	Execute setup (Button)
$\mathrm{f_{INT}}_{0102}$	Execute begin simulation (Button)
$\mathrm{f_{INT}}_{0103}$	Execute go once, *i.e.* run simulation for a tick (Button)
$\mathrm{f_{INT}}_{0104}$	Execute spring layout once (Button)
$\mathrm{F_{INT}}_{02}$	UI for Seed Settings
$\mathrm{f_{INT}}_{0201}$	Store On or Off (Switch) for Random Seed
$\mathrm{f_{INT}}_{0202}$	Store Seed value if random seed is off (Numerical Input)
$\mathrm{F_{INT}}_{03}$	UI for Smoothness S^* Model for Landscape Generation
$\mathrm{f_{INT}}_{0301}$	Store on/off, generalized NK model (Switch)
$\mathrm{f_{INT}}_{0302}$	Store Smoothness S^*value when on (Slider Input)
$\mathrm{F_{INT}}_{04}$	UI for NK Model for Landscape Generation
$\mathrm{f_{INT}}_{0401}$	Store on/off, specified NK model (Switch)
$\mathrm{f_{INT}}_{0402}$	Store N value when on (Numerical Input)
$\mathrm{f_{INT}}_{0402}$	Store *K* value when on (Numerical Input)
$\mathrm{F_{INT}}_{05}$	UI for Parametric Value Function for Landscape Generation
$\mathrm{f_{INT}}_{0501}$	Store on/off, value function input (Switch)

Table 4.7 Elements of the *Cgp* Composing the C²D Interface (Continued)

$f_{INT_{0502}}$	Store parameter A (Numerical Input)
$f_{INT_{0503}}$	Store parameter β (Numerical Input)
$f_{INT_{0504}}$	Store parameter α (Numerical Input)
$F_{INT_{06}}$	UI for Collaboration Dynamics
$f_{INT_{0601}}$	Store allowable diversity, m (Slider Input)
$f_{INT_{0602}}$	Store team size, n (Slider Input)
$f_{INT_{0603}}$	Store probability of a newcomer, p (Slider Input)
$f_{INT_{0604}}$	Store propensity to repeat a collaboration, q (Slider Input)
$f_{INT_{0605}}$	Store maximum-downtime, mdt (Slider Input)
$F_{INT_{07}}$	UI for Collaboration Strategies and Key Variables
$f_{INT_{0701}}$	Store fitness goal (stopping-criteria), o to 1 (Slider Input)
$f_{INT_{0702}}$	Store on/off for primary strategy (i.e. a composite of age-natural selection, hill climbing, mdt, and coalesce) [Switch]
$f_{INT_{0703}}$	Store on/off, allow only one final solution (Switch)
$f_{INT_{0704}}$	Store on/off, dynamic diversity saw-tooth function (Switch)
$f_{INT_{0705}}$	Store diversity tick increase for dynamic cases (Slider Input)
$f_{INT_{0706}}$	Store on/off, stop diversity if average ADMU fit (Switch)
$f_{INT_{0707}}$	Store on/off, stop prolonged decision making (Switch)
$f_{INT_{0708}}$	Store management pressure per tick increase for cases of reducing prolonged decision making (Slider Input)
$f_{INT_{0709}}$	Store on/off, allow long jumps (radical innovation) [Switch]
$f_{INT_{0710}}$	Store on/off, stop diversity if any ADMU fit (Switch)
$f_{INT_{0711}}$	Store on/off, annealing (e.g. system engineers) [Switch]

This switches, buttons, and sliders each primarily serve to inform other *cgp's* of the model. These mechanism and sub-mechanisms provide the key instructions for the running of the model and simulation. An example of their use follows in Table 4.8.

Table 4.8 Descriptor for Establishing the Model Seed through the C²D User Interface, $F_{INT_{02}}$

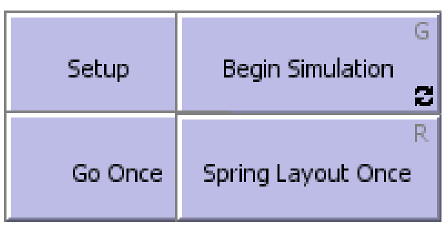
Unique Binary for *Cgp*	Unique Binary Identifier for the Transformation Function Involved	Input 1 (0001)	Input 2 (0010)	State Description
0011	0010	On/Off Random Seed Switch State	Value	State of the transformation function described below.
$F_{INT_{02}}$				

The described mechanism in Table 4.8 above stores the current state of the user input regarding the use of a random seed. If the user selects “On” for the random seed, the described mechanism generates a seed, an integer between 0 and 9999, at random. If the user selects “Off” for the random seed, the procedure replaces the random-seed native NetLogo parameter with the user-defined input. The procedure as implemented in the code follows:

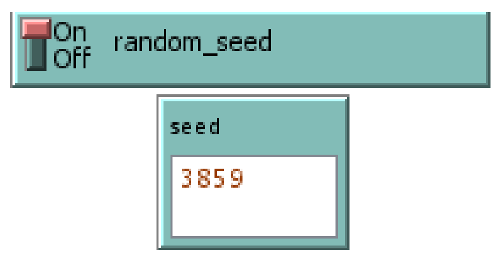
```
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
;;;;  Assign a seed to the model
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;

ifelse random_seed
    [ set seed random 9999 random-seed seed ]  ;; random-seed (pseudo-random number) takes integer
    [ random-seed seed ] ;; if not random set the random-seed to the user defined numerical input
```

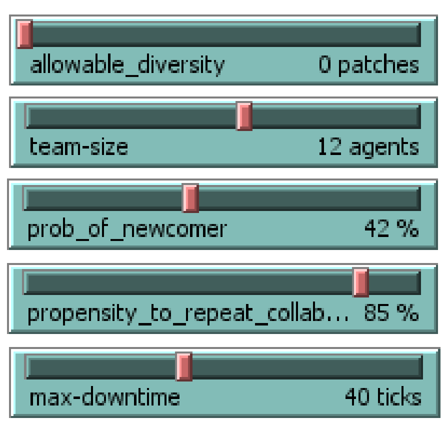
An example of these UI inputs follows in Figure 4.5. This figure demonstrates each of the types of interfaces used (i.e. numerical inputs, switches, buttons, and sliders). This figure also highlights specific mechanisms addressed in the preceding table and example.



Buttons ($F_{INT_{01}}$)



Switches and Numerical Inputs ($F_{INT_{02}}$)



Slider Inputs ($F_{INT_{06}}$)

Figure 4.5 Examples of User Inputs in the Interface *Cgp* (C_{INT})

Using the inputs from the users interfaces, the strategy mechanism and collaboration dynamics drive the ADMU and it exploration of the design landscape (similarly formed from the user inputs and discussed in Section 4.2.1). We subdivide the remaining procedures of the C^2D model to deal specifically at the ADMU level and its understanding of its environment, the collaboration specific dynamics level that determine the characteristics of the ADMU networks formed, and the implementation of the design strategies that drive the ADMU across the design landscape. We begin in the next section describing the ADMU, and more specifically how the ADMU communicates its understanding of the design landscape. Similar to the *cgp's* for the user interface, the following *cgp* similarly provides information regarding each individual ADMU and their own unique calculations performed at each tick of the simulation.

4.2.4 C^2D ADMUs

The individual ADMU must understand its own relationship to the environment and make that information available to the wider DAU collaboration. We define this DAU collaboration as the population of these ADMUs. As part of the ADMUs *cgp's* we include procedures that aggregate the data compiled at the individual ADMU level relevant to the overall functioning of the DAU. The primary mechanisms and sub-mechanisms that compose the functionality of the individual and DAU are described below in Table 4.9.

Table 4.9 Elements of the *Cgp* Composing the ADMUs, C_{ADMUs}

***Cgp* & Mechanism**	**Description**
$C_{ADMUs} = \sum_{i=1}^{n} \sum_{j=1}^{m} F_{ADMUs_{ij}}$	The relationship between the ADMUs and the DAU with regard to its operating environment is composed of the key functions shown below:
$F_{ADMUs_{01}}$	Calculate and Report Individual Characteristics
$f_{ADMUs_{0101}}$	Calculate and report number of links (i.e. collaborations)
$f_{ADMUs_{0102}}$	Calculate and report type of links (i.e. collaborations)
$f_{ADMUs_{0103}}$	Calculate and report length of links (in patches)
$f_{ADMUs_{0104}}$	Calculate and report if at an optima on the landscape
$f_{ADMUs_{0105}}$	Calculate and report if move increased fitness (Appendix N)
$f_{ADMUs_{0106}}$	Calculate and report ticks while exploring (not on solution)
$f_{ADMUs_{0107}}$	Calculate and experience (e.g. newcomer, incumbent)
$f_{ADMUs_{0108}}$	Calculate and report age (i.e. longevity in the collaboration)
$f_{ADMUs_{0109}}$	Calculate and report downtime (time since being in a team)

Table 4.9 Elements of the *Cgp* Composing the ADMUs (Continued)

$f_{ADMUs_{0110}}$	Calculate and report current fitness
$f_{ADMUs_{0110}}$	Calculate and report current fitness of neighboring patches
$F_{ADMUs_{02}}$	Calculate and Report Statistics for the DAU
$f_{ADMUs_{0201}}$	Calculate and report number of incumbents
$f_{ADMUs_{0202}}$	Calculate and report number of incumbent-incumbent links
$f_{ADMUs_{0203}}$	Calculate and report number of newcomers
$f_{ADMUs_{0204}}$	Calculate and report number of incumbent-newcomer links
$f_{ADMUs_{0205}}$	Calculate and report number of links
$f_{ADMUs_{0206}}$	Calculate and report the average fitness of ADMUs
$f_{ADMUs_{0207}}$	Calculate and report the minimum fitness of ADMUs
$f_{ADMUs_{0208}}$	Calculate and report the maximum fitness of ADMUs
$f_{ADMUs_{0209}}$	Calculate and report the average fitness of ADMUs on team
$f_{ADMUs_{0210}}$	Calculate and report the average fitness of incumbents
$f_{ADMUs_{0211}}$	Calculate and report the size of the largest component
$f_{ADMUs_{0212}}$	Calculate and report the size of the smallest component
$f_{ADMUs_{0213}}$	Calculate and report the number of components
$f_{ADMUs_{0214}}$	Calculate and report the time to stopping-fitness for average
$f_{ADMUs_{0215}}$	Calculate and report the time to stopping-fitness for team
$f_{ADMUs_{0216}}$	Calculate and report the time from beginning of design
$f_{ADMUs_{0217}}$	Calculate and report minimum link lengths
$f_{ADMUs_{0218}}$	Calculate and report maximum link lengths
$f_{ADMUs_{0219}}$	Calculate and report average link lengths
$f_{ADMUs_{0220}}$	Calculate and report average clustering coefficient
$f_{ADMUs_{0221}}$	Calculate and report number of repeat collaborations

The described mechanisms in Table 4.9 above utilizes a series of reporter procedures in NetLogo. These mechanisms take the current inputs to the calculation (e.g. number of turtles) and reports the resulting calculated values with each tick. These procedures generally follow a similar implementation as described in the following code example:

```
;;;;  Report average fitness for all turtles, f_ADMUs_0206
    to-report avg_fitness
      report mean [fitness] of turtles
    end

;;;;  Report number of links,  f_ADMUs_0205
    to-report link_count
      report count links
    end
```

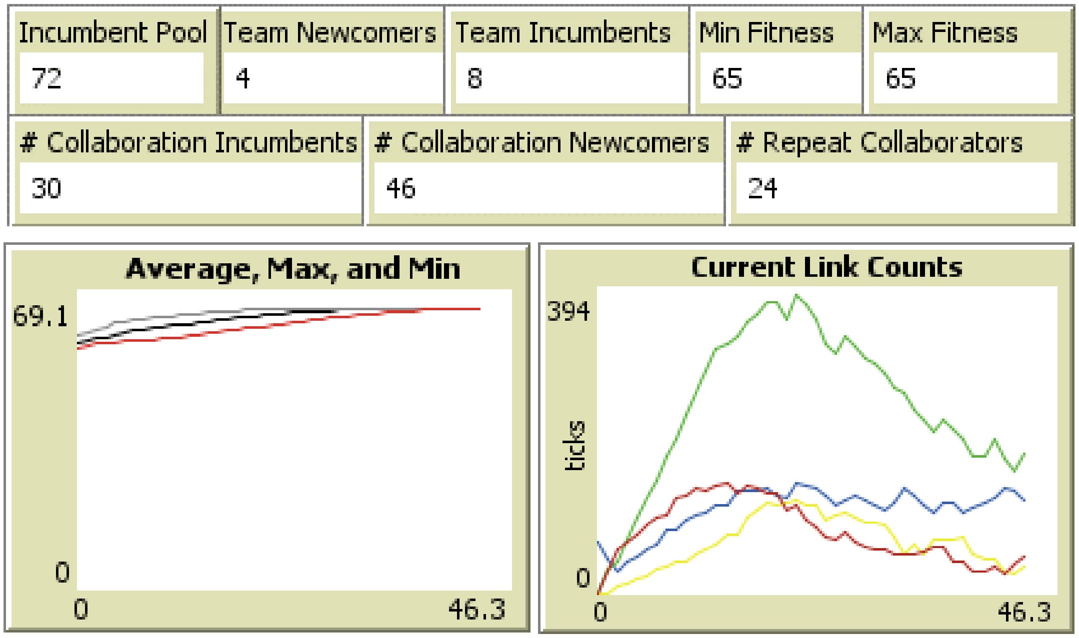


Figure 4.6 Displaying Reporters in the C^2D Model

The procedures provide outputs to other *cgp's* as well as to the analyst and user through the interface. Figure 4.6 illustrates an example of the representation of the data to the user. This display updates at each tick to represent the current state of each measure. The top portion of this figure shows an example numeric display shown to the user in the interface while the bottom figure shows a graphical representation of the sample data also made available to the user in the interface.

4.2.5 C^2D Collaboration Dynamics

A core component of the C^2D model centers on how the design-team forms and comes together. We have previously discussed the various inputs required for these dynamics to occur, such as the probability of incorporating a newcomer, the propensity of a team-member to repeat a collaboration, the team-size used in a collaboration, and the maximum-downtime allowable for a design team. These dynamics utilize inputs from the user interface *cgp's* discussed in Section 4.2.3. As discussed in Chapter 2, we select these particular parameters and dynamics to reflect findings from Guimerà et al. 2005 that suggest these parameters drive the overall performance of collaborative efforts. We build on these particular dynamics to incorporate the concept of diversity explicitly in the model. These collaboration dynamics govern the way that agents join a collaboration and how they leave. We capture these dynamics below in Table 4.10.

Table 4.10 Elements of the *Cgp* Composing the Collaboration Dynamics, C_{COL}

***Cgp* & Mechanism**	**Description**
$C_{COL} = \sum_{i=1}^{n} \sum_{j=1}^{m} F_{COL_{ij}}$	The collaboration dynamics in the model is composed of the key functions shown below:
$F_{COL_{01}}$	Team forms
$f_{COL_{0101}}$	Assign Newcomers and Incumbents - Draw random number and compare to the probability of newcomer (p)
$f_{COL_{0102}}$	Place Newcomers - Randomly place any newcomer to the team randomly up to the allowable diversity limit (m)
$f_{COL_{0103}}$	Assign Incumbent Type– For incumbents, draw random number and compare to propensity to repeat collaboration $(q)$to determine if collaboration is new or a repeat
$f_{COL_{0104}}$	Repeat until desired team-size (n) achieved
$f_{COL_{0105}}$	Assign links between new team members
$F_{COL_{02}}$	ADMUs leave the collaboration
$f_{COL_{0201}}$	Expire – If an agent has not participated on a design team past the maximum downtime (mdt) they will leave (i.e. attrite)
$f_{COL_{0202}}$	Intervening for Underperformers - If an agent persists in a non-satisficing design location on the landscape they will be less likely to reproduce (natural selection), *i.e.* they die out in proportion to their fitness through a random draw. This only works if enabled through the corresponding strategy (aging / natural selection dynamic).

We capture each of these collaboration dynamics through their mechanisms as described in their descriptor seen in Table 4.11 and Table 4.12. These descriptors highlight the inputs required for each of these procedures.

Table 4.11 Descriptor for Establishing the Model Seed through the C²D User Interface, $F_{INT_{02}}$

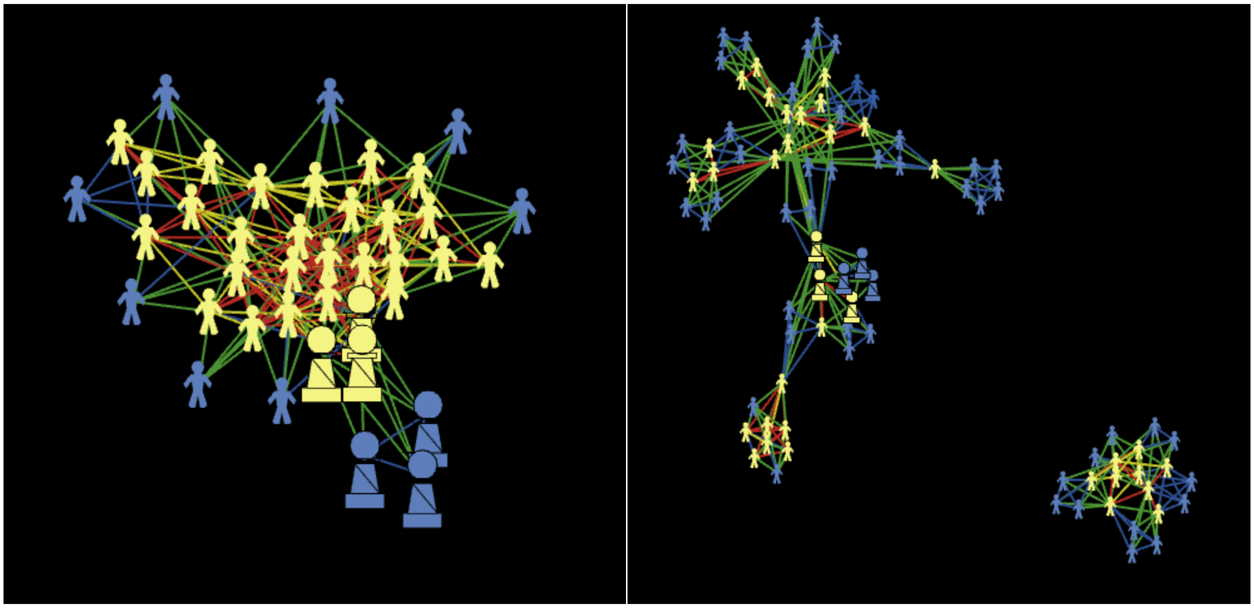
Unique Binary for *Cgp*	Unique Binary Identifier for the Transformation Function Involved	Input 1	Input 2	Input 3	Input 4
0101	0001	p	q	n	m
$F_{COL_{01}}$		State Description			
		State of the transformation function described below.			

Table 4.12 Descriptor for Establishing the Model Seed through the C²D User Interface, $F_{INT_{02}}$

Unique Binary for *Cgp*	Unique Binary Identifier for the Transformation Function Involved	Input 1	Input 2	Input 3	Input 4
0101	0010	age	downtime	mdt	fitness
$F_{COL_{02}}$		Input 5	State Description		
		fitness goal	State of the transformation function described below.		

Both of these highlighted mechanisms take their respective inputs and work together to transform these inputs into the resulting collaboration structures seen in C^{2}D. The C_{COL} procedures utilize inputs derived or collected from C_{INT} and C_{ADMUs} in its operation. In the instance of $F_{COL_{01}}$, the procedure transforms the user inputs regarding how the collaboration comes together to resulting in fully formed and connected teams on the design landscape. Similarly, $F_{COL_{02}}$uses its inputs to counterbalance this growth, limiting the overall collaboration size by removing underperforming ADMUs and allowing disinterested parties (i.e. those who haven't be engaged in a team within a certain period specified by the maximum-downtime) to leave the collaboration. We build on code from McAvity (2006) to introduce a natural selection dynamic ($f_{COL_{0202}}$) and code from Bakshy and Wilensky (2007) to implement the linkages and team-formation dynamics required by $F_{COL_{01}}$. We supply an example of the code implementation for $F_{COL_{01}}$ in the appendix (cf. Appendix O) and the $F_{COL_{02}}$ dynamics as follows:

```
;;;;  Leave through attrition or management pressure / natural selection, F_COL02
   to leave_collaboration
     ask turtles  ;;;;  NetLogo term for agent, in C2D these are ADMUs
     [  if age? and ( fitness < ( (random-float Management_Pressure) * stopping-fitness ) ) and ( ( age )
     > random (fitness) and (downtime >= 1)  )     [die]
     ;;;; Only punish for performance if natural selection strategy is enabled, i.e. age? ( f_STR0101)
     ;;;; Allow some learning curve before punishing underperforming, i.e. age must be greater than
      some random value between 0 and its current fitness value (fitness ranges from 0 to 100).
     ;;;; Ensure team-member don't die out (i.e. if you are on the team you can pursue something unfit).
     set in-team? false
     set age age + 1 ]
    [  if max-downtime? and (downtime > max-downtime) ;;;; Attrition (f_STR0102)
    ;;;; Only punish if max-downtime is a strategy and it is above the max downtime (mdt)
     [die]
     set in-team? false
     set downtime downtime + 1 ]
   end
```



n = 6, *p* = 20%, *q* = 100%, *m* = 10, *mdt* = 40 (*fitness goal* 92%, *seed* 898, *time* 24 ticks) | *n* = 6, *p* = 50%, *q* = 100%, *m* = 10, *mdt* = 40 (*fitness goal* 92%, *seed* 898, *time* 24 ticks)

Figure 4.7 Example of Collaboration Dynamics in C_{COL}

These collaboration dynamics drive the formation of the collaboration and its network, as seen in Figure 4.7. We now look to procedures for applying these collaboration formation dynamics on the landscape. More specifically, we examine procedures to guide the movement of the DAU in its search for fitness. To do this we consider *cgp's* for capturing the *design strategies* behind the DAU and its collaboration.

4.2.6 C²D Design Strategies

By definition, the process of engineering design involves purpose and the thoughtful construction of solutions to problems. In our framework, design represents the matching of design parameters and functional requirements in the search of sufficing fitness. We consider design strategies as a series of rules or procedures to maximize the fitness of a DAU. The design strategies we investigate allow us to develop insights into ways potentially to enable designers to overcome a rugged design landscape (i.e. a landscape with varying levels of fitness corresponding to the ability of design possibilities to meet requirements). In the most general sense, fitness corresponds to the ability of an entity to survive (Rumelt, Schendel and Teece 1991). We more specifically view fitness and as a measure of the ability of a design configuration (i.e. the match of design parameters to functional requirement) to satisfice functional requirements. We highlight the central *cgp* (C_{STR}) we investigate for enabling the DAU to achieve fitness as part of Table 4.13.

Table 4.13 Elements of the *Cgp* Composing the Collaboration Dynamics, C_{COL}

***Cgp* & Mechanism**	**Description**
$C_{STR} = \sum_{i=1}^{n} \sum_{j=1}^{m} STR_{ij}$	The collaboration dynamics in the model is composed of the key functions shown below (we also include a brief description of the intuition and analogue to engineering design):
$F_{STR_{01}}$	Basic Meta-Strategy (Default)
$f_{STR_{0101}}$	Age? (Natural Selection in Management), this strategy allows agents to age, if enabled then $f_{COL_{0202}}$takes the increasing age as an input in deciding who leaves the collaboration based on their current performance.
$f_{STR_{0102}}$	Maximum-downtime? (Attrition), this strategy allows agents to accrete downtime when unengaged, if enabled then $f_{COL_{0201}}$uses the amount downtime accrued for each ADMU as an input in deciding who leaves the collaboration.
$f_{STR_{0103}}$	Hill Climbing? (Incremental Innovation), this strategy drives each ADMU navigation of the design landscape by considering its neighboring fitness landscape locations (e.g. similar design concepts to the one at its current location) and then proceeding to the one with the best fitness of the neighbors.
$f_{STR_{0104}}$	Coalesce? (Group Consensus and Exploitation), this strategy allows the group to limit its willingness to incorporate discrepant ideas (e.g. newcomers with a different conceptual focus) when the group has found a sufficiently fit design concept to exploit.
$F_{STR_{02}}$	Require Same Stopping Point (Final Design Position Required)
$F_{STR_{03}}$	Dynamic Diversity (Group Adapts its Diversity Acceptance)
$F_{STR_{04}}$	Cease Bringing in Diversity when Average Fitness is Sufficient
$F_{STR_{05}}$	Cyclical Diversity (Grow Diversity to Maximum, then Restart)
$F_{STR_{06}}$	Long Jumps as an Analogue for Radical Innovations
$F_{STR_{07}}$	Stop Recruiting Newcomers with Diversity if Any Designer is Fit
$F_{STR_{08}}$	Simulated Annealing as an Analogue to Systems Engineering

In our base runs for C^2D, we ensure that the basic meta-strategy given by $F_{STR_{01}}$ remains consistently structured over each of the simulation runs. In short, we assume that engineering design and the DAU operate according to a minimum set of guiding influences, namely:

- How well designers (i.e. ADMUs) perform (including how well management responds to this) influences their ability to recruit new team-members to the DAU (cf. $f_{STR_{0101}}$)

- Designers must remain actively engaged in the collaboration or they may leave the DAU after some period of time of inactivity (cf. $\mathrm{f}_{\mathrm{STR}_{0102}}$)

- Most design processes resemble an exploration of concepts relative to an existing conceptual loci (i.e. initial set of conditions or concepts), in turn resembling a process conceptually similar to hill climbing on the theoretical design landscape (cf. $\mathrm{f}_{\mathrm{STR}_{0103}}$)

- Designers limit their exploration of design concepts as acceptable design solutions emerge (cf. $\mathrm{f}_{\mathrm{STR}_{0104}}$)

We describe this particular basic strategy mechanism $\mathrm{F}_{\mathrm{STR}_{01}}$in Table 4.14 below. This mechanism uses inputs related to guide the way that the DAU forms teams (expanding the collaboration) and how the ADMUs explore the design landscape. We use the additional strategies to explore the influence of allowing increased exploration versus exploitation on the design landscape, allowing more diversity in the backgrounds of new team-members to the DAU, and dynamic management strategies to shape the skill-set and backgrounds of a team over time. These strategies each represent a tailoring either to the stopping conditions for the simulation (e.g. all ADMUs must be on the same design concept at conclusion of the simulation) or to the abilities of the DAU or ADMU in its team-formation and exploration activities (e.g. changes in diversity to newcomers, ability to pursue radical exploration).

Table 4.14 Descriptor for Establishing the Model Seed through the C²D User Interface, $\mathrm{F}_{\mathrm{INT}_{02}}$

<table>
<tr><th>Unique Binary for Cgp</th><th colspan="2">Unique Binary Identifier for the Transformation Function Involved</th><th>Input 1</th><th>Input 2</th><th>Input 3</th><th>Input 4</th></tr>
<tr><td>0110</td><td colspan="2">0001</td><td>age</td><td>downtime</td><td>mdt</td><td>fitness</td></tr>
<tr><td rowspan="2">$\mathrm{F}_{\mathrm{STR}_{01}}$</td><td>Input 5</td><td>Input 6</td><td>Input 7</td><td>Input 8</td><td>Input 9</td><td>State Description</td></tr>
<tr><td>neighboring patch fitness</td><td>average DAU fitness</td><td>management pressure</td><td>allowable diversity</td><td>fitness goal</td><td>State of the transformation function described above.</td></tr>
</table>

4.3 C^2D Model and Formalisms Conclusion

Each of the *cgp's* described as a part of this chapter form the basis of the C^2D model. Although we cover the core dynamics and aspects of the model through these procedures, we direct the author to the complete NetLogo code for completeness and implementation specifics beyond the scope of the discussion above. These procedures, comprised of their mechanisms and sub-mechanisms, use the discussed inputs from the model and analyst to provide a theoretical representation of a design landscape and the DAU complex-adaptive socio-technical system. By fusing these procedures and the possible set of inputs provided by the model and its interface, we arrive at a framework for exploring design in the broader context of an interplay between the user, the designer, and the technology artefact. This framework allows us to represent and trace observable behaviors and characteristics from the model during any future simulations. As part of the explorations of this research and the framework presented, we have extrapolated well-known search strategies from operations research (Winston and Goldberg 2004). These search strategies provide the research an initial starting ground for explore strategies relevant to design. As part of the exploration, we tie these search strategies, through analogy, to strategies and concepts relevant to engineering design. It is expected that this initial framework can aid continued research to better enable the decision-maker in the actual decision making processes of engineering design and in better describing the actual patterns of seen in the behaviors of engineering design practitioners observed in the real world.

5

Experimental Approach and Observations

"There are two possible outcomes: if the result confirms the hypothesis, then you've made a measurement. If the result is contrary to the hypothesis, then you've made a discovery."

- Enrico Fermi

The previous chapter explains the *Complex Adaptive Performance Evaluation Method for Collaborative Design* (C^2D) model and its implementation. In short, this model provides the analyst and experimenter a tool for jointly exploring design complexity and design performance. The C^2D model represents the complexity of a design through a fitness landscape derived from the underlying number of functional requirements (N) and their interdependencies (K) as discussed in Chapter 3. Similarly, the model relates design performance to the ability of the designer, artefact, and user (DAU) complex adaptive socio-technical system, comprising a set of individual agent-based decision-making units (ADMUs), to explore the design landscape and find sufficiently fit solutions. Strategies guide the DAU during its search of the design landscape. In terms of game theory, strategies form a finite set of options from among which players (in our instance ADMUs) can choose. As in game theory, the fitness outcomes of these strategies depends on the underlying problem space (in our instance the design landscape), as well as both the individual actions of the ADMUs and the collective actions of the DAU. In the C^2D case, the experimental approach includes comparing the success of individual design strategies and different design strategy combinations, as well as variations to the performance of the DAU under different design-team assembly and landscape parameterizations. The C^2D framework measures success in terms of the fitness characteristics of the DAU and the search-times required by the DAU to achieve sufficiently fit design solutions. To simplify the experimental approach, the selection of strategies remains constant throughout each simulation, *i.e.* the strategies employed remain the same and perfectly inherited among the ADMUs throughout each of the simulations.[41] By comparing the performance characteristics resulting from variations to parameterizations and strategies, over the course of multiple simulations and different seed conditions, the analysis tests for underlying statistical significance between these relationships. The research uses these tests to confirm or reject the research and null hypotheses described in Chapter 1.

5.1 Hypothesis Testing

The objective of this section is to test the research questions posed by the individual hypotheses in Chapter 1 for statistical and practical significance. The current section follows with a discussion of each hypothesis and some clarifying rationale, the design of the experiment surrounding the hypothesis, a discussion of the testing methodology used, and finally the results and observations from the statistical tests used. The research follows the analysis of these individual hypotheses with overall findings and policy recommendations from the overall research in the following chapter. Each of the following experiments relies on simulating results across multiple design landscapes. To eliminate the bias introduced by the particular seed used, the analysis selects multiple seeds at random to average the results across (i.e. it runs several replications of every measurement with different random number seeds). In order to have replicability of results the analysis also compares these simulation results to simulations using a constant set of 100 randomly generated seeds. The analysis checks for any discrepancies in the statistical findings between these seed sets. Table 5.1 captures these randomly selected seeds.

[41] In traditional game theory, the interactions between two rational agents are considered, *i.e.* each agent assumes the other will act rationally in order to maximize their own pay-off. Nowak (2006) points out that in the case of evolutionary games, agents do not necessarily need to assume rationality or themselves act rationally; the only requirement is that the agents (i.e. players) have a strategy. General explorations of evolutionary games focus on the frequency of adoption of strategies within a group and its relationship to the underlying growth or culling of a population. In evolutionary games the success of one strategy, especially relative to another, arises through the mechanism of evolution and its performance relates to its ability to reproduce. Similar to the replicator function in evolutionary game theory that enables reproduction, Chapter 4 discusses the replication mechanics in C^2D model as part of the collaboration mechanisms $F_{COL_{01}}$ and $F_{COL_{02}}$. Future work and extensions of the C^2D model begins to explore the concept of varying the preference sets of designers and examining the differences in the strategies they choose to adapt over the course of a simulation.

Table 5.1 Randomly Selected Seed Set (Common Random Numbers Technique)

12934	12614	5557	4397	6925	714	16502	15385	4821
3361	6775	16115	4181	1617	5221	13468	3139	17670
13670	2335	9385	7870	12437	15816	3824	18670	11291
4210	17373	5136	10171	7210	9054	6198	7294	4857
16321	3891	7711	8221	14749	8498	5925	14194	2747
12076	1934	27519	2804	1253	15044	321	6796	17139
1482	4099	8293	2861	10318	15471	8197	3956	8771
3822	6142	3385	16646	3929	17859	3830	3963	4494
2323	21464	17620	486	5923	3482	4658	22362	9252
4846	471	6145	3033	8612	13291	3337	6336	13529
26927	9494	2557	19711	22291	1097	8065	1586	18971

Each of these seeds influences the overall stochastic elements in the model, to include the generation of a unique design landscape (i.e. each seed results in a unique landscape). For consistency, the analyses ensure the use of these same randomly selected seeds in each of the following experiments for comparison purposes. This technique follows from the common random numbers technique discussed by Banks (1998). As a result, the following experiments require a minimum number of simulations equivalent to 100 times the number of individual parameter changes. The analysis also runs each simulation using a set of random seeds to allow for the detection of any sensitivities to the seed set (in these instances the analysis requires multiple repetitions using different seeds). The analysis evaluates each hypothesis using the random-seed and common random numbers for each of the possibilities highlighted in Table 5.2. For purposes of simplicity, the analysis reports the statistics from the random seed set and documents any discrepancies, if any, between the two seed sets. The analyses use the Type 1 error rate and Type 2 error rate specified in the table for the test of the individual hypotheses.

Table 5.2 Possible Outcomes of Statistical Tests

		State of World	
		H_o	H_a
Decision	H_o	Correctly Accept the Null Hypothesis ($p = 1 - \alpha < .95$)	Type II Error (False Negative) ($p = \beta = 0.2$)
	H_a	Type I Error (False Positive) ($p = \alpha = .05$)	Correctly Reject the Null Hypothesis ($p = 1 - \beta > .8$)

5.1.1 *Hypothesis 1 – Team Formation and Performance*

The first question posed by the research was whether changes to the team-formation parameters resulted in statistically significant differences to the overall search performance of the DAU, specifically its final design fitness values and search-times. Although the research recognizes that additional parameters outside of team-assembly drive the performance of teams, the research structured the C^2D model around these parameters from Guimerà, Uzzi, Spira, and Amaral (2005) as a basis. The research choose this starting point due to its relative simplicity and the significance found between the key parameters of team-assembly and the overall performance of collaborative teams. This study suggests that the dynamics surrounding how teams come together plays a large role in the final performance characteristics of a collaboration. In particular, the parameters of most interest adapted from that study, based on their explanatory potential, included the probability of a team to incorporate a newcomer, the propensity of a team to repeat collaboration, the overall team-size, and the maximum-downtime a past collaborator will wait when unengaged before leaving the effort. Using this information, the research first tests the following hypothesis:

Alternative Hypothesis 1: Varying the team-formation dynamics (i.e. the probability of incorporating a newcomer (p), the propensity of team-members to repeat collaborations (q), the overall team-size (n) embedded in the larger collaboration, and the maximum-downtime (mdt) for a previous collaborator) of a design-team leads to significant differences in the average design-team fitness values ($\overline{f_t}$) and the search-time for the design-team (t_s).

$$\left|\frac{\partial \overline{f_t}}{\partial n}, \frac{\partial \overline{f_t}}{\partial p}, \frac{\partial \overline{f_t}}{\partial q}, \frac{\partial \overline{f_t}}{\partial mdt}\right| > 0 \quad \wedge \quad \left|\frac{\partial t_s}{\partial n}, \frac{\partial t_s}{\partial p}, \frac{\partial t_s}{\partial q}, \frac{\partial t_s}{\partial mdt}\right| > 0 \qquad H_{a_1}$$

Null Hypothesis 1: Varying the team-formation dynamics (i.e. the probability of incorporating a newcomer (p), the propensity of team-members to repeat collaborations (q), the overall team-size (n) embedded in the larger collaboration, and the maximum-downtime (mdt) for a previous collaborator) of a design-team does not lead to significant differences in the average design-team fitness values ($\overline{f_t}$) and the search-time for the design-team (t_s).

$$\left|\frac{\partial \overline{f_t}}{\partial n}, \frac{\partial \overline{f_t}}{\partial p}, \frac{\partial \overline{f_t}}{\partial q}, \frac{\partial \overline{f_t}}{\partial mdt}\right| = 0 \quad \wedge \quad \left|\frac{\partial t_s}{\partial n}, \frac{\partial t_s}{\partial p}, \frac{\partial t_s}{\partial q}, \frac{\partial t_s}{\partial mdt}\right| = 0 \qquad H_{o_1}$$

5.1.1.1 Design of Experiments

The analysis structures the test of the hypothesis by individually evaluating the possible relationships between performance and each of the stated parameters. During these tests, all of the remaining parameters and strategies remain constant between the runs. Specifically, this means that the parameterizations of the runs follow the configuration shown in Table 5.3. The table marks the parameters that vary in the experiments. These parameter values represent the default parameters of the model as discussed in Chapter 3 and as implemented in Chapter 4.

Table 5.3 Default Parameter Settings for Runs for Hypothesis 1

Smoothness (N=13, K=6)	50%
Allowable Diversity (m) at Start	50 patches
Fitness Goal	92%
Default Modelling Dynamics (Age?, Max-Downtime?, Hill-Climbing?, and Coalesce?)	On
Require Same Stopping Point Strategy (Consensus)	Off*
Dynamic Diversity (Saw-Tooth Profile) Strategy	Off
Stop Diversity if Average of the DAU is Fit Strategy	Off
Pause and Restart Diversity Strategy	Off
Stop Prolonged Decision Making Strategy	Off
Initial Management Pressure	1.0 dmnl
Team-size (n) *	4 ADMUs
Probability of Newcomer (p)*	42%
Propensity to Repeat a Collaboration (q)*	85%
Maximum-Downtime (mdt)*	40 ticks

** Varied as specified in the individual experiments for Hypothesis 1 below.*

5.1.1.1.1 Team-Size Experiment

In the instance of the team-size (n), the research structures a design of experiments to examine the average fitness values of design-teams ($\overline{f_t}$) and their search-times (t_s) under various team-sizes. This test examines small teams to very large teams, and compares the effect of different team-size parities (odd-sized teams versus even-sized teams). The design of experiments for team-size follows in Table 5.4 for illustrative purposes and its more compact equivalent in Table 5.5. The remaining hypotheses utilize the compact representation from Table 5.5 and omit the pre-set duplicate runs. This basic experimental setup results in 2,000 simulations.

Table 5.4 Fitness Values and Stopping Time for Various Seeds, Complexity Values, and Team-Sizes

Seeds	Team-Size (n)	Intermediate K ($S = 50\%$)	
		f_t	t_s
$Seed_1$	2		
	3		
	⋮		
	15		
⋮	⋮	⋱	
$Seed_{100}$	2		
	3		
	⋮		
	15		

Table 5.5 Behavior Space Implementation in Simulation for Hypothesis 1: Team-Size

Test using common numbers seed-set	
n	[“team-size” [2 1 21]]
Seed	["seed" seed-set]
S	[“smoothness” 50]]
Commands	Setup, Go

Notation: [Variable [LL, increment, UL]]

Test using random numbers	
n	[“team-size” [2 1 21]]
Seed	["seed" random]
S	[“smoothness” 50]]
Repetitions	100
Commands	Setup, Go, Repeat

5.1.1.1.2 Probability of Incorporating Newcomer Experiment

In the instance of the parameter probability of a newcomer (p), the analysis similarly structures a design of experiments to examine its relationship (if any) to the average fitness values of design-teams ($\overline{f_t}$) and their search-times (t_s). The experiment examines a wide range of probabilities, while avoiding extreme cases where teams are strictly newcomers or incumbents. The experiment also consider the degree of complexity on the landscape to ensure there are no interaction effects. The design of experiments for the discussed results, as done in subsequent hypotheses, follows below in Table 5.6. The ensuing experimental setup results in 2,600 simulations.

Table 5.6 Behavior Space Implementation in Simulation for Hypothesis 1: Probability of Newcomer

p	["prob_of_newcomer" [20 5 80]]
Seed	["seed" random]
S	[“smoothness” 10 50]
Repetitions	100
Commands	Setup, Go, Repeat

5.1.1.1.3 Propensity for Repeating a Collaboration Experiment

For the propensity to repeat a collaboration (q) parameter, the analysis structures a design of experiments to examine the average fitness values of design-teams ($\overline{f_t}$) and their search-times(t_s) for various likelihoods (i.e. propensities) for collaborating with an incumbent. The experiment structures the range of tested values to reflect the likely values for the DAU based on observations from Guimerà et al. (2005) in other creative and scientific collaboration types. The design of experiments follows a similar setup as used earlier, except that it enforces the need for consensus in decision-making. The experiment enforces the need for consensus as the role of repeating collaborations influences the cohesiveness of teams, which in turn only significantly influences performance when the DAU requires a consensus solution. In order to allow for the timely runs given the computational requirements for this setup, the analyses reduce the number of repetitions; the analysis verifies that any significance remains supported by the observed power in the test. The overall setup follows below in Table 5.7. This experimental setup requires 620 simulations.

Table 5.7 Behavior Space Implementation in Simulation for Hypothesis 1: Repeating Collaborations

q	["prop_to_repeat" [70 1 100]]
Seed	["seed" random]
S	[“smoothness” 10 50]
Repetitions	10
Commands	Consensus, Setup, Go, Repeat

5.1.1.1.4 Maximum-Downtime Experiment

Similarly, the analysis structures an experiment to measure the sensitivity of performance to the maximum-downtime parameter (mdt). The experiment examines the average fitness values of design-teams ($\overline{f_t}$) and their search-times (t_s) for various parameter settings. The analysis examines its sensitivity across multiple variables to capture any interaction effects. The design of experiments follows below in Table 5.8. This experimental setup results in 11,880 simulations.

Table 5.8 Behavior Space Implementation in Simulation for Hypothesis 1: Maximum-Downtime

mdt	["max-downtime" [10 5 60]]	S	[“smoothness” 10 50]
p	["prob_of_newcomer" 20 50 80]	Seed	["seed" random]
q	["prop_to_repeat" 20 50 80]	Repetitions	20
Team-size	[“team-size” 2 3 6 7 10 11]	Commands	Setup, Go, Repeat

5.1.1.2 Testing Methodology

The experimental testing first removes outliers (more than 3-sigma) from the data before applying an analysis of variance (ANOVA) for testing the relationships posed by hypothesis one. ANOVA is a collection of statistical models used to analyze differences among group means and characteristics of groups (e.g. variations). The ANOVA process generalizes the Student's t-test to allow for the comparison of more than two groups. These models enable testing for statistically significant difference between the means of a population (Bailey 2008). This F-test compares each of the factors of the total deviation. This test provides an "omnibus" test to detect significance between any of parameters and their means, but does not provide insight into what parameters vary significantly. The F-test statistic for a one-way test follows in equation (5.1), as stated by Conover (1980) below:

$$F = \frac{MS_T}{MS_E} = \frac{SS_T/df_T}{SS_E/df_E} = \frac{SS_T/(I-1)}{SS_E/(n_t-I)} = \frac{\sum n(x-\bar{x})^2/I-1}{\sum(n-1)\sigma^2/n_t-I} \tag{5.1}$$

Where:

MS_T, mean sum of squares due to treatment	I, total number of treatments
MS_E, mean sum of square due to error	n_t, total number of cases
SS_T, sum of squares due to treatment	n, treatment sample size
SS_E, sum of squares due to error	σ, standard deviation of samples
df_T, degree of freedom for group	x, observed value of sample
df_E, degree of freedom for error	$\bar{x}$, mean value of samples

Assuming that the significance (probability corresponding to the F-statistic) found in our analysis remains less than the critical value of alpha (α) of the study, the analysis finds a statistically significant effect. This testing methodology and analytical procedure allows the research to determine statistical significance for the hypothesis. These tests either confirm the null hypotheses or reject the null hypotheses in favor of the alternative hypothesis. In this case, significance implies an effect where the means differs more than would be expected from chance alone. When significance is determined (as well as adequate power), the analysis also employs a series of post-hoc tests, to include the conservative Tukey test, which runs multiple comparisons between means to identify individual effects between factors of a variable (Huber 2011). These tests help to provide the analysis specificity to any of the significance found between variables where required, *e.g.* a particular team-size (such as four) has a significant statistical effect on the average fitness of the DAU.

In addition to one-way ANOVA tests, the analysis performs a series of test to examine the possibility of between-subject effects (i.e. interactions between variables) using an overall comparison between the factors using a Multivariate ANOVA (MANOVA), while also testing that homogeneity of variances exists within the test populations. The analysis performs these tests primarily using the IBM Statistical Package for the Social Sciences (SPSS). The analysis includes measures of the effect size of these statistics, *i.e.* the quantitative measure of the strength of an effect. These effect size measures provide an interpretation of the substantive significance, versus statistical, significance of a result (Ellis 2010). For each of these measures, a larger absolute value always indicates a stronger effect. To determine this measure the analysis calculates the proportion of total variability attributable to the partial eta squared (η^2). The equation for this measure, as stated by Kelly and Preacher (2012), in the case of univariate tests follows in equation (5.2) below:

$$\eta^2 = \frac{SS_{effect}}{SS_{total}} = \frac{SS_{effect}}{SS_{effect} + SS_{error}} \tag{5.2}$$

Where:

SS_{effect}, sum of squares of effect SS_{error}, sum of squares of error
SS_{total}, total sum of squares for all effects, interactions, and errors in the ANOVA

Similarly, the analysis also measures the observed or statistical power for any analysis. This power represents the probability of correctly rejecting the null hypothesis and corresponds to the likelihood for correctly accepting the alternative hypothesis in Table 5.2. As this power increases, the chances of a Type II error (false negative) decreases. Ultimately, this measure helps to ensure that the research has employed an adequate sample size (i.e. number of simulations) to adequately detect any effect. This relationship between the power of a test and the false negative rate follows from Cohen (2013) in equation (5.3) below:

$$power = 1 - \beta = P(reject\ H_o | H_o\ is\ false) = P(accept\ H_a | H_a\ is\ true) \tag{5.3}$$

Where:

β, the false negative rate

Finally, in the case of some investigations, the analysis also makes use of nonparametric tests to include the related-samples Wilcoxon Signed Rank Test for significance and the Spearman's Rho Rank Correlation for strength. These tests allow us to detect significance between two related samples, matched samples, or repeated measurements and their strength using nonparametric data. In particular, the Wilcoxon Signed-Rank Test provides a nonparametric alternative test of significance that assesses whether the population mean ranks differ (Lowry 2014).

5.1.1.3 Results and Observations

In the following section, the analysis examines the results of each of the statistical analyses performed, using each of the design of experiments highlighted above. The goal of these tests is to determine the statistical significance, if any, of the relationship between the identified team-formation parameters on the final fitness values and search-times of the DAU, as stated in the preceding hypotheses.

5.1.1.3.1 Test for Team-Size and DAU Performance Relation

In the instance of the team-size (n), the analysis applies the testing methodology to the data collected from the design of experiment described earlier (cf. Section 5.1.1.1). The analysis examines the mean fitness of a design-team ($\overline{f_t}$) and the time (t_s) to achieve the fitness objective (i.e. the search-time) under different team-sizes. The ANOVA test reveals statistically significant relationships for both accounts. The summary results of the overall experiment follow in Table 5.9 and Table 5.10. The overall statistical results of the experiment appear in Appendix Q. Additionally, a plot of the estimated marginal means (i.e. the means for each parameterization over all simulations) for each of these significant findings follows in Figure 5.1 below.

Table 5.9 Summary of Test of Between-Subjects Effects for Team-Size for Hypothesis 1

Source	Dep. Var.	Type III Sum of Squares	df	Mean Square	F (19,1980)	Sig.	η^2	Noncent. Parameter	Obs. Power[a]
	$\overline{f_t}$	7018.742	19	369.407	22.435	.000	.177	426.264	1.000
	t_s	35935.992	19	1891.368	3.721	.000	.034	70.692	1.000

a. Observed Power $(1-\beta)$ computed using alpha = .05

Table 5.10 Hypothesis Test for Team-Size for Hypothesis 1

Null Hypothesis	Test	Sig.	Decision
The mean difference among the means of $\overline{f_t}$ for different values of n equals 0.	ANOVA F-test	.000	Reject the null hypothesis.
The mean difference among the means of t_s for different values of n equals 0.	ANOVA F-test	.000	Reject the null hypothesis.

Asymptotic significances are displayed. The hypothesis test uses an alpha of 0.05.

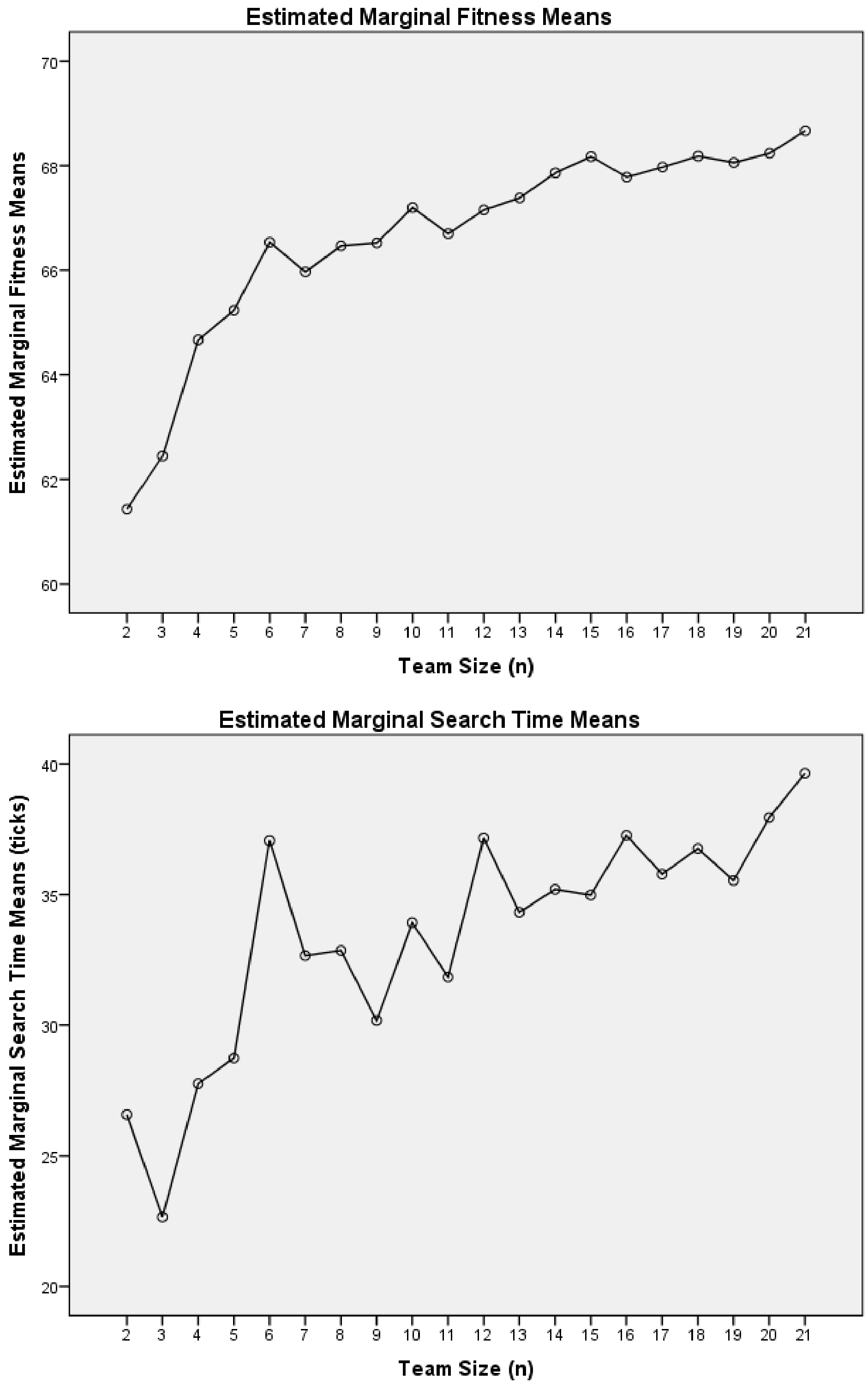


Figure 5.1 Estimated Marginal Means for Statistically Significant Team-Size Relationships for Hypothesis 1.1. The characteristics of the performance response to changing team-sizes depends on the degree of complexity in the design landscape. This graph shows the notional case from the design of experiments of a relatively smooth design ($S^* = 50\%$) surface corresponding to $K = 6$ and $N = 13$.

Although outside the scope of the original hypothesis, the analysis considers the influence of the consensus process for different team-sizes (as seen in Appendix Q.1). For instance, the correlation between performance and team-size rises with the requirement for consensus to a moderately strong correlation (i.e. Spearman's Rho correlation of 0.418 for mean fitness and 0.190 for search-times). This new data set also includes each of the variables as dependents in its calculation simultaneously, resulting in over 11,000 simulations. Additionally, these tests examine the idea that even-sized teams and odd-sized teams may have different impacts on the overall performance of the DAU. The research bases this research premise on work from Menon and Phillips (2011) that found even-sized small groups often experience lower cohesion than odd-sized small groups. Through this test, the analysis determined that the effect of parity (even or odd) in a team-size was statistically significant for the given team-sizes from the experiment when consensus was required and not significant in the absence of a consensus process. Table 5.11 summarizes these findings. The analysis similarly provides the overall test in the appendix (Q.3). Further, regardless of parity or consensus requirements, the final fitness values for the various team-sizes did not consistently demonstrate significant differences for the tested design landscape and DAU parameters. However, due to the stopping condition in the simulation using a preset fitness objective, this finding is consistent with the implementation of the model and highlights the nuances of goal setting or objective setting in the case of value-based design (i.e. outcomes will likely not greatly exceed design expectations and objectives). If a management system defines arbitrary objectives, the DAU will work to achieve solutions near these objectives – resulting in weakly significant or insignificant deviations between the objective and final fitness values. This effect maybe desirable in the case of reasonably set objectives, however, if objectives are overly relaxed then even a relatively close to acceptable design may require complete rework in the face of even slight shifts to the value and fitness objective.

Table 5.11 Hypothesis Test for Team-Size Parity in Hypothesis 1

<table>
<tr><th></th><th>Null Hypothesis</th><th>Test</th><th>Sig.</th><th>Decision</th></tr>
<tr><td rowspan="2">Consensus Required</td><td>The median of differences between $\overline{f_t}$ for team-sizes of different parity equals 0.</td><td>Related-Samples Wilcoxon Signed Rank Test</td><td>.000</td><td rowspan="2">Reject the null hypothesis.</td></tr>
<tr><td>The median of differences between t_s for team-sizes of different parity equals 0.</td><td>Related-Samples Wilcoxon Signed Rank Test</td><td>.002</td></tr>
</table>

Asymptotic significances are displayed. The hypothesis test uses an alpha of 0.05.

The overall results for team-size suggest that by optimizing a team's overall size for a given design landscape and for its structural complexity, the DAU can potentially device policies that maximize its performance by matching team-size to the complexity of a design and to the design objectives. Conceptually, with a greater number of team-members comes a greater number of resources to achieve design objectives and a more diverse and thorough exploration of the design landscape. However, as team-size increases so too do the opportunities for conflicts and communication challenges within the DAU. These challenges can decrease the cohesion and productivity of the DAU. As part of Hypothesis 4, the analysis examines the possibility of optimal team-sizes existing given the complexity of a task. The research notes that odd versus even team-sizes, especially in the case of smaller teams, remains a valid topic for continued future research based on the preliminary findings from these initial tests. Team-size, alone, however, remains just one variable. The experience and relationships among the team greatly contributes to the success of the DAU. One of the key issues behind this relative skill composition and the homogeneity of a team and its stability in the C^{2}D model comes in the ability of a team to bring in newcomers, which is the subject of the next parameter test performed.

5.1.1.3.2 Test for Newcomers and DAU Performance Relation

In the instance of the probability of incorporating a newcomer (p), the analysis similarly examines the mean fitness of a design-team $(\overline{f_t})$ and the time (t_s) to achieve the fitness objective under different probabilities of incorporating a newcomer. The ANOVA test reveals statistically significant relationships for both accounts. The summary results of the overall experiment follow in Table 5.12 and Table 5.13. The overall statistical results of the experiment appear in Appendix R. Additionally, the analysis provides the estimated marginal means for each of the significant findings as part of the appendix.

Table 5.12 Summary of Test of Between-Subjects Effects for Probability to Incorporate a Newcomer in Hypothesis 1

Source	Dep. Var.	Type III Sum of Squares	df	Mean Square	F (12,2574)	Sig.	η^2	Noncent. Parameter	Obs. Power[a]
p	$\overline{f_t}$	2078.660	12	173.222	6.894	.000	.031	82.727	1.000
	t_s	1530474.422	12	127539.535	2.055	.017	.009	24.661	.937

a. Observed Power $(1-\beta)$ computed using alpha = .05

Table 5.13 Hypothesis Test for Probability to Incorporate a Newcomer in Hypothesis 1

Null Hypothesis	Test	Sig.	Decision
The mean difference among the means of $\overline{f_t}$ for different values of p equals 0.	ANOVA F-test	.000	Reject the null hypothesis.
The mean difference among the means of t_s for different values of p equals 0.	ANOVA F-test	.017	Reject the null hypothesis.

Asymptotic significances are displayed. The hypothesis test uses an alpha of 0.05,

The results of the statistical tests suggest that the ability of a team to recruit newcomers has a significant role in the success of the DAU. The recruitment of newcomers influences team performance in several ways. For example, the addition of a newcomer decreases the degree of stability among existing team members, leading to significant swings in the search-times and average fitness values of the DAU. This factor conceptually leads to decreases in the cohesiveness of the DAU by introducing new opinions that, depending on the allowable diversity, may represent radically different design approaches from existing team-members. However, conversely, the increased heterogeneity among the team also helps to improve performance by minimizing groupthink and highlighting divergent design possibilities and different feasible design approaches with potentially superior fitness.

5.1.1.3.3 Test for Propensity to Repeat Collaborations

The analysis examines the mean fitness of a design-team ($\overline{f_t}$) and the time (t_s) to achieve the fitness objective under different propensities for repeating a collaboration (q). The analysis achieves this through a design of experiments that examine the expected DAU ranges for q based on the literature, i.e. a propensity to repeat collaborations ranging from 70 to 100. The overall statistical findings are included as part of Appendix S. The summary of the results follows in Table 5.14 and in Table 5.15.

Table 5.14 Summary of Test of Between-Subjects Effects for Propensity to Repeat a Collaboration in Hypothesis 1

Source	Dep. Var.	Type III Sum of Squares	df	Mean Square	F (30,509)	Sig.	η^2	Noncent. Parameter	Obs. Power[a]
q	$\overline{f_t}$	3500.545	30	116.685	7.072	.000	.294	212.153	1.000
	t_s	3519603.240	30	117320.108	2.715	.000	.138	81.444	1.000

a. Observed Power $(1-\beta)$ computed using alpha = .05

Table 5.15 Hypothesis Test for Propensity to Repeat a Collaboration in Hypothesis 1

Null Hypothesis	Test	Sig.	Decision [a b c]
The mean difference among the means of $\overline{f_t}$ for different values of q equals 0.	ANOVA F-test	.000	Reject the null hypothesis.
The mean difference among the means of t_s for different values of q equals 0.	ANOVA F-test	.000	Reject the null hypothesis.

a. Asymptotic significances are displayed. The hypothesis test uses an alpha of 0.05.
b. Reject the null hypothesis only for the given range tested for q between 70 and 85%.
c. Significance only found when consensus in the simulation was required.

The ANOVA reveals a statistically significant relationship between the propensity to repeat a collaboration and the average fitness values of the DAU and its search-time. The results of the analysis suggest that the propensity of a team to repeat its collaborations has a statistically significant role in the success of the DAU, however, more detailed analysis reveals that this degree of significance only holds true for certain ranges for the q parameter. More particularly, the significance demonstrates sensitivities for values outside of the range used in the test.

The propensity of a team-member to decide to collaborate with a team-member whom they have previously engaged, influences the homogeneity of the team while also reinforcing the role identity of a selected member. When talking about team homogeneity, the C^2D model refers to the degree to which members on the design-team are similar; in our model this corresponds to the clustering (C) within the DAU, *i.e.* how tightly, compacted members of the DAU remain. Similarly, reinforced role-identity typically limits the diversity of exploration of the landscape. With an increased propensity to repeat collaborations, there is a statistically significant relationship between this overall clustering of the DAU, both for the average clustering $(\overline{C_t})$ and the final clustering (C_t). The summary of these tests follow in Table 5.16 and Table 17. Similarly, the overall statistical test were also included in the appendix (S.3).

Table 5.16 Summary of Test of Between-Subjects Effects for Propensity to Repeat a Collaboration and Clustering in Hypothesis 1

Source	Dep. Var.	Type III Sum of Squares	df	Mean Square	F (30,434)	Sig.	η^2	Noncent. Parameter	Obs. Power[a]
q	C_t	.080	30	.003	2.434	.000	.144	73.030	1.000
	$\overline{C_t}$	.048	30	.002	3.096	.000	.176	92.873	1.000

a. Observed Power $(1-\beta)$ computed using alpha = .05

Table 5.17 Hypothesis Test for Propensity to Repeat a Collaboration and Clustering in Hypothesis 1

Null Hypothesis	Test	Sig.	Decision
The mean difference among the means of $\overline{C_t}$ for different values of q equals 0.	ANOVA F-test	.000	Reject the null hypothesis.
The mean difference among the means of C_t for different values of q equals 0.	ANOVA F-test	.000	Reject the null hypothesis.

Asymptotic significances are displayed. The hypothesis test uses an alpha of 0.05.

Although outside the bounds of the original statistical test, conceptually the propensity to repeat collaborations, demonstrated by clustering, also speaks to the comfort of designers to continue working with one another and the stability of the DAU. Stability in the context of the C^{2}D model encompasses more than just a measurement of turnover (measured as the number of incomers entering the DAU and the number of incumbents leaving the DAU per tick): it includes the degree of comfort and trust that members of the DAU place in one another. The research relates this degree of trust indirectly through this clustering of the DAU. The role of the manager of the DAU and a key purpose of the C^{2}D model is to find ways to balance this cohesiveness of the design-team (i.e. its clustering) against groupthink and the need for diversity.

5.1.1.3.4 Test for Maximum Downtime and Performance Relation

In the instance of the maximum-downtime (mdt), the analysis again structures the experiment to examine the average fitness of a design-team ($\overline{f_t}$) and the time (t_s) to achieve the fitness objective under different parameter values. As part of this testing the analysis examines mdt in five tick increments between 10 and 60 ticks. The overall statistical findings are included as part of Appendix T. The summary of the results highlights a statistically significant relationship between mdt and average fitness and search-times for the DAU as outlined below in Table 5.18 and in Table 5.19.

Table 5.18 Summary of Test of Between-Subjects Effects for Team-Size in Hypothesis 1

Source	Dep. Var.	Type III Sum of Squares	df	Mean Square	F (10,10687)	Sig.	η^2	Noncent. Parameter	Obs. Power[a]
mdt	f_t	110.211	10	11.021	.578	.834	.001	5.776	.310
	$\overline{f_t}$	1089.939	10	108.994	5.815	.000	.005	58.154	1.000
	t_s	1095570.673	10	109557.067	2.046	.025	.002	20.460	.898

a. Observed Power $(1-\beta)$ computed using alpha = .05

Table 5.19 Significance and Hypothesis Test for Maximum Downtime in Hypothesis 1

Null Hypothesis	Test	Sig.	Decision [a b]
The mean difference among the means of $\overline{f_t}$ for different values of mdt equals 0.	ANOVA F-test	0.00	Reject the null hypothesis.
The mean difference among the means of t_s for different values mdt equals 0.	ANOVA F-test	.025	Reject the null hypothesis.

a. Asymptotic significances are displayed. The hypothesis test uses an alpha of 0.05.
b. Statistical significance for search-time only valid when consensus is not required.

As with the q parameter, the relationship between the mdt parameter and both the average fitness and search-times of the DAU has a complex relationship over the range of all possible values. Although the resulting means for design performance vary significantly with changes to the mdt, the overall relationship remains weakly correlated. Additionally, the sensitivity of the parameter levels off after a certain point, *i.e.* if the test is ran using values for mdt starting at 40 ticks (instead of starting at 10 ticks) the parameter loses significance. Given the dynamics of the DAU and the C^2D model, this relationship conceptually makes sense. Continued access to underutilized designers plays an increasingly less significant role in an existing collaboration when the overall pool of potential collaborators remains sufficiently large and sufficiently diverse (i.e. with the correct skill specializations). However, if too many of these designers opt to leave a collaboration at once or too many leave prematurely the stability of the team suffers (in effect contributing to turnover). In effect, the mdt within the DAU helps to regulate not only the size characteristics of the DAU collaborations but also the resulting composition of expertise levels available to the team up to a point. It does so by helping to regulate the stability of the team, in turn bringing about normalcy and the patterns of emergence seen in the collaboration characteristics of the DAU. This increased stability also provides the possibility of improved group cohesion, better communication, and more effective role management.

5.1.2 Hypothesis 2 - Newcomers and Final Fitness

After confirming the existence of a statistically significant relationship between the design-team parameters and fitness, the next central research question dealt with the nature of the possible benefits and costs to the final fitness associated with incorporating too little or too many newcomers to the DAU collaboration. In order to see if there was in fact an inflection point where too many newcomers negatively affected performance, the hypothesis tests for a quadratic trend over a specific range of values. Specifically, the analysis tests for an inverted U-shaped relationship between the probabilities of incorporating newcomers (p) on a team and the final fitness attained by the team (f_t) as specified in the design of experiments. The resulting alternative and null hypotheses follow:

Alternative Hypothesis 2: There exists an inverted U-shaped relationship between the likelihood of newcomers (p) on a design effort and the final design-team fitness (f_t).

$$\lambda p \approx -{f_t}^2, \quad \lambda = \text{constant scalar} \qquad H_{a_2}$$

Null Hypothesis 2: There does not exist an inverted U-shaped relationship between the likelihood of newcomers (p) on a design effort and the final design-team fitness (f_t).

$$\lambda p \not\approx -{f_t}^2, \quad \lambda = \text{constant scalar} \qquad H_{o_2}$$

5.1.2.1 Design of Experiments

For the probability to incorporate a newcomer (p) parameter, the analysis again structures a design of experiments to examine the final fitness values of design-teams (f_t) for various probabilities. In the experiment, all of the parameters and strategies remain constant between the runs according to the configuration shown below in Table 5.20. The design of experiments follows a similar setup as used earlier, and follows below in Table 5.21. This experimental setup again results in 465 simulations.

Table 5.20 Default Parameter Settings for Runs for Hypothesis 2

Smoothness (N=13, K=6)	50%
Allowable Diversity (m) at Start	50 patches
Fitness Goal	90%
Default Modelling Dynamics (Age?, Max-Downtime?, Hill-Climbing?, and Coalesce?)	On
Require Same Stopping Point Strategy (Consensus)	Off
Dynamic Diversity (Saw-Tooth Profile) Strategy	Off
Stop Diversity if Average of the DAU is Fit Strategy	Off
Pause and Restart Diversity Strategy	Off
Stop Prolonged Decision Making Strategy	Off
Initial Management Pressure	1.0 dmnl
Team-size (n)	4 ADMUs
Propensity to Repeat a Collaboration (q)	85%
Maximum-Downtime (mdt)	40 ticks

Table 5.21 Behavior Space Implementation in Simulation for Hypothesis 2

p	["prob_of_newcomer" [70 1 100]]	Repetitions	15
Seed	["seed" random]	Commands	Setup, Go, Repeat
S	["smoothness" 50]]		

5.1.2.2 Testing Methodology

As before, the analysis performs a one-way ANOVA, which in this case examines the parameter p and the final fitness values f_t for the design-team in order to determine the statistical significance of any relationship. Again, the ANOVA allows the analysis to compare the dependent variable of final fitness values f_t to different values of the probability to incorporate a newcomer p. As before, SPSS treats the independent variable p as a categorical measure in these instances. However, unlike testing in the previous hypothesis the analysis specifically uses trend analysis to contrast the expected linear trend model to a polynomial trend model. In effect, the model appends a squared term to the linear regression equation in the case of a quadratic fit, as follows below in equation (5.4):

$$\overline{Y}_{j_{quadratic}} = b_0 + b_1 X_j + b_2 {X_j}^2 \tag{5.4}$$

Where:

b_0, constant
b_1, linear coefficient
b_2, quadratic coefficient
X_j, independent variable
${X_j}^2$, squared value for independent variable

5.1.2.3 Results and Observations

The overall statistical findings and plots of the mean final fitness values are included as part of Appendix U. The summary of the results demonstrates a statistically significant quadratic trend as highlighted in Table 5.22 and in Table 5.23.

Table 5.22 Final Fitness Values Trend Testing and Significance for Hypothesis 2

Final Fitness (f_t) for p		Sum of Squares	df	Mean Square	F (30, 434)	Sig.
Quadratic Term	Contrast	207.837	1	207.837	4.464	.035
	Deviation	1022.458	28	36.516	.784	.779

Table 5.23 Significance and Hypothesis Test for Hypothesis 2

Null Hypothesis	Test	Sig.	Decision [a b c]
The mean difference among the means of f_t for different values of p^2 equals 0.	ANOVA F-test	0.035	Reject the null hypothesis

a. Asymptotic significances are displayed. The hypothesis test uses an alpha of 0.05.
b. Reject the null hypothesis only for the given range tested for p between 70% and 100%
c. The overall research hypothesis is not supported over the entire range for p

For the given range of p and the level of complexity used in the simulations, the findings represent a statistically significant result that there does exist a quadratic trend with regard to the average final fitness values f_t among the different probabilities to incorporate a newcomer p. As seen in Table 5.22, the quadratic trend is statistically significant and the test of whether there is a trend more complex than quadratic is not significant, *i.e.* the deviation significance for the quadratic trend, which implies no further complex trends exists. However, when examining the parameter over all possible values from zero to one there does emerge a cubic or higher ordered trend, *i.e.* more than the two sign changes present in a quadratic relationship. These changes occur in the relative centers of the lower (i.e. 0% to 33%), middle (i.e. 33% to 66%), and upper regions (i.e. 66% to 100%) of p values. Therefore, the results only partially supports the original hypothesis as posed, *i.e.* it only holds true for specific conditions. One explanation of this trend follows from the anticipated behaviors associated with established relationships and the disruptive potential of a newcomer.

For example, these trend behaviors suggest that for well-established teams (i.e. made entirely of incumbents) the introduction of a newcomer can be difficult. Within these established teams, existing relationships help guide the activities of the DAU and the introduction of a singular or even relatively small number of new designers can lead to the loss of team performance. In part, this behavior stems from the DAU effort to incorporate the newcomer, which corresponds to unproductive effort spent aligning the newcomer to the wider collaboration (i.e. their perspective and conceptual locus, their location on the design landscape). However, after a certain tipping point newcomers begin to play a larger role in the exploration activities of the landscape, *i.e.* they begin to influence the conceptual locus of the overall DAU. Although this raises the search-times, it leads to improved design outcomes and the improved average fitness of the DAU as seen in Hypothesis 1. These newcomers raise this average fitness by ensuring that the DAU explores a larger portion of the design possibility space than otherwise possible. However, yet another inflection point exists where without any cohesion the DAU becomes chaotic, searching completely at random. Although a completely random walk of the design landscape may lead to more competing design approaches, without any cohesion the DAU becomes less likely to discern the best design approach from these design approaches. More simply, without a sufficient basis of designers at any one solution, the outcomes from management selection (an analogue to the natural selection mechanic) ultimately become less likely to select the best solution.

Interestingly, these fitness trends exist across each of the identified regimes for likelihood values, *i.e.* low, middle, and upper. The research views these regimes as resulting from stable periodic relationships between the DAU members that undergo long complicated behaviors before repeating, where the likelihood of incorporating a newcomer represents a chaotic fluctuation to these relationships. In other words, this parameter p provides the ability to move the DAU to a higher or lower relative state of fitness, however, this relationship remains complex. The results demonstrate significant changes to the final fitness of the DAU resulting from changes to the willingness and probability of a team to incorporate newcomers. However, the likelihood of incorporating newcomers only partially describes the overall disruptiveness of their contribution to the DAU. For example, adapting conceptually aligned members (i.e. no diversity) results in minimal disruption compared to that of a highly diverse newcomer, the subject of the next hypothesis.

5.1.3 Hypothesis 3 – Diversity and Final Fitness

The third hypothesis deals with the exploration of diversity and its influence on performance. As part of this inquiry, the research focuses on the relationship between the allowable diversity of newcomers, final fitness values achieved, and the best theoretical design solution available. The analysis equates the global maximum on the design landscape to the best theoretical design solution. This allows the analysis to examine final fitness values achieved by the DAU with respect to their global maxima. By measuring these relative fitness values at different levels of diversity, the research explores the question of whether diversity on a team can help the DAU achieve better design solutions, in effect preventing design fixation or the premature convergence on a design approach. The analysis examines this question in terms of the following research hypothesis:

Alternative Hypothesis 3: Increasing the level of diversity among newcomers (m) in the design-team has a positive relationship with the prevention of design fixation as measured by the ratio of the final fitness values of the design-team (f_t) to the global fitness maximum (f_m).

$$\left(f_t/f_m\right)\Big|_{m_1} \quad < \quad \left(f_t/f_m\right)\Big|_{m_2} \; for \;\; m_1 > m_2 \qquad\qquad H_{a_3}$$

Null Hypothesis 3: Increasing the level of diversity among newcomers (m) in the design-team does not have a positive relationship with the prevention of design fixation as measured by the ratio of the final fitness values of the design-team (f_t) to the global fitness maximum (f_m).

$$\left(f_t/f_m\right)\Big|_{m_1} \quad \nless \quad \left(f_t/f_m\right)\Big|_{m_2} for \;\; m_1 > m_2 \qquad\qquad H_{o_3}$$

5.1.3.1 Design of Experiments

For multiple values of allowable diversity (m), the analysis again structures a design of experiments to examine the final fitness values of design-teams (f_t) relative to their theoretical maximum (f_m). The design of experiments follows a similar setup as used earlier, and follows below in Table 5.24 and Table 5.25. This experimental setup results in 750 simulations.

Table 5.24 Default Parameter Settings for Runs for Hypothesis 3

Fitness Goal	90%
Default Modelling Dynamics (Age?, Max-Downtime?, Hill-Climbing?, and Coalesce?)	On
Require Same Stopping Point Strategy (Consensus)	Off
Dynamic Diversity (Saw-Tooth Profile) Strategy	Off
Stop Diversity if Average of the DAU is Fit Strategy	Off
Pause and Restart Diversity Strategy	Off
Stop Prolonged Decision Making Strategy	On
Initial Management Pressure	1.0 dmnl
Team-size (n)	4 ADMUs
Probability of Incorporating a Newcomer (p)	50%
Propensity to Repeat a Collaboration (q)	85%
Maximum-Downtime (mdt)	40 ticks

Table 5.25 Behavior Space Implementation in Simulation for Hypothesis 3

m	["allowable_diversity" [0 10 140[a])]]	Repetitions	25
Seed	["seed" random]	Commands	Setup, Go
S	[“smoothness” 10 90]		

a. The diagonal of the design landscape.

5.1.3.2 Testing Methodology

As before, the analysis begins by first performing a one-way ANOVA to ensure that there exists a statistically significant relationship in the data, which in this case includes examining the relationship between the allowable diversity parameter m and the ratio of final fitness values f_t to maximum fitness values f_m. After establishing significance, the analysis then compares correlations using multiple regression models to determine the best fit for the trend (e.g. linear, quadratic), its relative significance, and the underlying sign of any relationships (i.e. negative or positive correlations). The analysis compares the correlations using the Pearson product-moment correlation coefficient (R).

5.1.3.3 Results and Observations

The ANOVA demonstrates a statistically significant relationship in the average ratio of fitness values (f_t) to global maximum fitness values (f_m) and the underlying allowable diversity in the DAU as seen in Table 5.26. The research includes the overall statistical findings for the ANOVA as part of Appendix U. However, as part of the hypothesis the analysis also investigates a reasonable model for the data. Based on the data and its plot as seen in Figure 5.2, the analysis adopts an S-curve logistic function model for the data. Table 5.27 details the S-curve model statistics and its significance. The analysis then creates a linear model equivalent by transforming the dependent variable from f_t/f_m to $\ln(f_t/f_m)$ and the independent variable from m to its inverse $1/m$. The analysis then carries out a final ANOVA for trends in Table 5.28. The results demonstrate a linear trend for our transformation and suggest no higher order trends exist, based on the standard deviation insignificance. Table 5.29 provides the overall finding.

Table 5.26 Summary of Test of Between-Subjects Effects for Diversity in Hypothesis 3

Source	Dep. Var.	Type III Sum of Squares	df	Mean Square	F (13, 686)	Sig.	η^2	Noncent. Parameter	Obs. Power[a]
m	f_t	1413.871	13	108.759	3.094	.000	.055	40.217	.996
	$\overline{f_t}$	400.213	13	30.786	1.353	.177	.025	17.587	.784
	t_s	3338259.927	13	256789.225	5.698	.000	.097	74.078	1.000
	f_m	107.502	13	8.269	.402	.969	.008	5.232	.244
	f_t/f_m	.149	13	.011	6.473	.000	.109	84.148	1.000
	$f_m - f_t$	1118.451	13	86.035	6.471	.000	.109	84.125	1.000

a. Observed Power $(1-\beta)$ computed using alpha = .05

Table 5.27 Model Summary for the S-Curve Logistic Approximation in Hypothesis 3

Model Summary

R	R Square	Adjusted R Square	Std. Error of the Estimate
.318	.101	.100	.047

The independent variable is m.

Coefficients

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
$1/m$	-.648	.073	-.318	-8.866	.000
(Constant)	-.014	.002		-5.853	.000

The dependent variable is $\ln(f_t\ /f_m)$.

ANOVA for Model

	Sum of Squares	df	Mean Square	F	Sig.
Regression	.172	1	.172	78.599	.000
Residual	1.531	698	.002		
Total	1.703	699			

The independent variable is m.

Table 5.28 ANOVA for the Linearized Approximation in Hypothesis 3

Dep. Var. $\ln(f_t\ /f_m)$ and Ind. Var. $(1\ /m)$			Sum of Squares	df	Mean Square	F	Sig.
Between Groups	(Combined)		.136	13	.010	3.726	.000
	Linear Term	Weighted	.128	1	.128	45.647	.000
		Deviation	.008	12	.001	.233	.997
Within Groups			.880	313	.003		
Total			1.016	326			

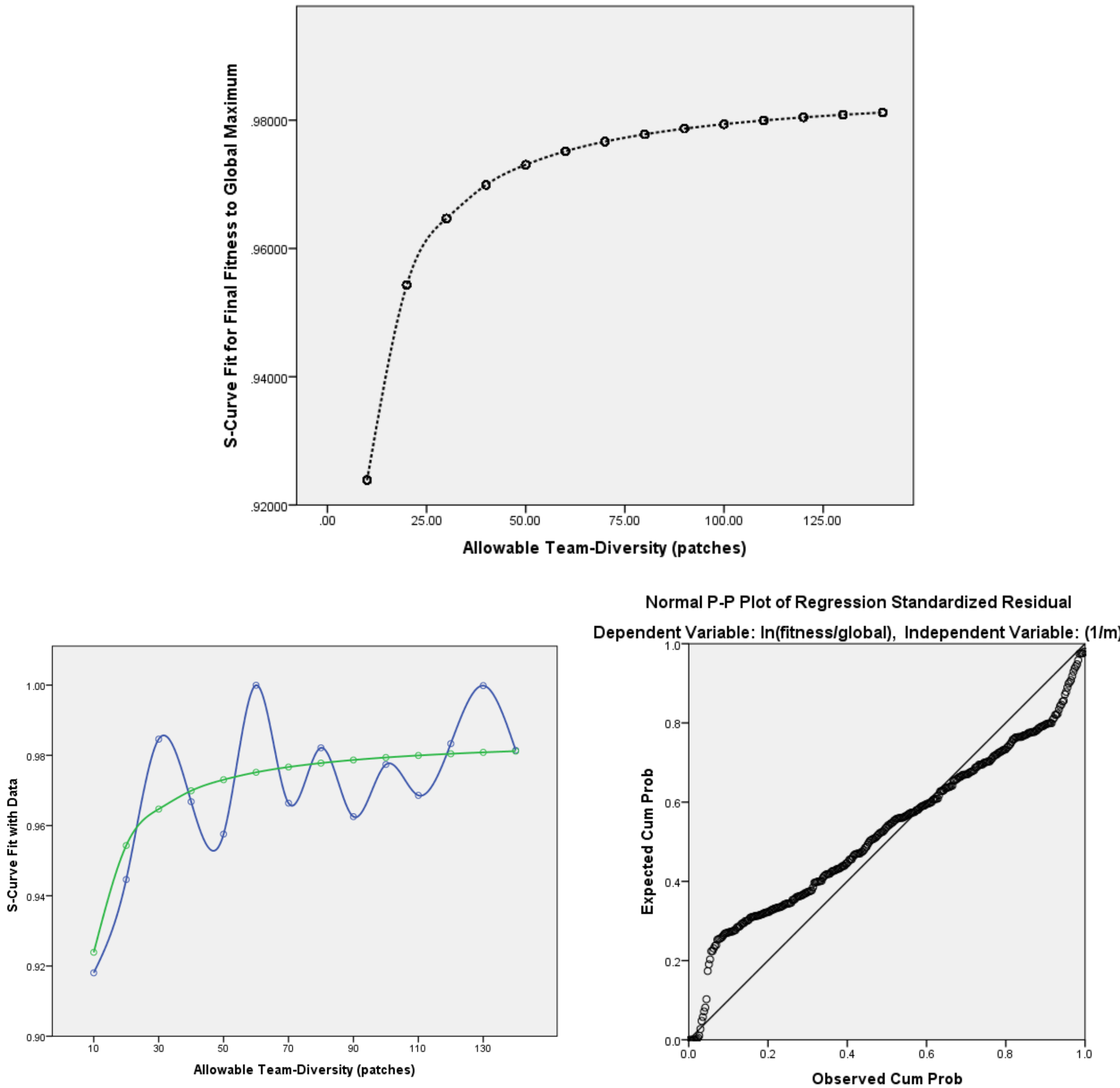


Figure 5.2 S-Curve Fit (top) and Fitted Data (bottom left) compared to P-P Plot of Fit (bottom right) for Hypothesis 3

The results demonstrate a reasonable linear fit for our transformation, suggesting that the logistic-function model provides an appropriate model for the data over the considered range. Figure 5.2 above demonstrates the curve fit for the model, an overlay of the actual data with the fit, and a plot of the observed versus expected cumulative probabilities for the transformed model. Given the statistically significant linear trend and moderate positive correlation in the transformed data, the analysis concludes that there is a positive relationship between variables and summarizes these overall finding in Table 5.29.

Table 5.29 Significance and Hypothesis Test for Hypothesis 3

Null Hypothesis	Test	Stat.	Decision
The mean difference among the means of for the ratio $\ln(f_t/f_m)$ for different values of $(1/m)$ equals 0.	ANOVA F-test	0.000 Sig.	Reject the null hypothesis.
The ratio $\ln(f_t\ /f_m)$ and $(1/m)$ is not positively correlated.	Pearson's R	0.318	Reject the null hypothesis. There is a moderate positive correlation in the data.

Asymptotic significances are displayed. The hypothesis test uses an alpha of 0.05.

The results confirm that diversity plays an important role in ensuring a thorough exploration of the overall design possibility space and in preventing the premature convergence of the DAU on lesser fit, even if sufficiently fit, design solutions. One of the insights derived in the analysis arises out of the observed logistical relationship seen in the data that suggests diversity of about 30 patches (approximately 22% of the maximum allowable diversity) yields marginal and diminishing returns for the DAU in terms of the final fitness values achieved relative to their theoretical maxima. However, most interestingly, the data does not show a statistically significant increase to the amount of search-time required for increases in diversity past 30 patches. Specifically, removing diversity values less than 30 from the data, as in Appendix V (cf. Table V.3), results in a loss of statistical significance for search-time. This is in part because the effect of diversity is restricted only to the newcomers entering the team. This finding has interesting implications for the inclusion of newcomers in real design-settings; for instance, having highly diverse newcomers can improve the ability of the team to locate new solutions without necessarily protracting the design process. This particular finding holds true for when the likelihood of adapting a newcomer remains less than or equal to 50%. Although it does not change the statistical findings, there were also interaction effects noted with the degree of complexity on the design landscape. In the next hypothesis, the research explores the role of complexity explicitly with regard to team-size.

5.1.4 *Hypothesis 4 – Do Ideal Team-Sizes Exist?*

As alluded to in Hypothesis 1, increased team-sizes have a significant influence on the performance components of engineering design, specifically the search-time and the average-fitness components of the DAU. Increases in the size of a team can raise the difficulty of communication within the DAU and even, at a certain point, result in an actual decrease to the productivity of the DAU. For the simulated design efforts, this translates in the data as a trend of diminishing returns to the productivity of the DAU for increased team-sizes. The analysis measures these returns to the design productivity using the marginal productivity of the DAU; more simply, it calculates how much a design improves its fitness relative to the total design effort (i.e. a designer-tick) for each additional team-member. This follows from the general relationship established by the marginal product of labor (MPL), *i.e.* $MPL = \Delta Output/\Delta Input$. Given the trend of quickly diminishing returns seen in the performance data, the research question focuses on whether there exists a maximum team-size (n^*) with respect to realizing further gains to design productivity. The test for a maximum team-size follows as part of the corresponding hypothesis:

Alternative Hypothesis 4: There exists a maximum team-size (n^*) before the marginal productivity of design becomes negative.

$$\frac{\partial P}{\partial n^*} > 0 \geq \frac{\partial P}{\partial n'} \forall \;\; n^* < n' \qquad H_{a_4}$$

Null Hypothesis 4: There does not exist a maximum team-size (n^*) before the marginal productivity of design becomes negative.

$$\frac{\partial P}{\partial n^*} = \frac{\partial P}{\partial n'} \forall \;\; n^* < n' \qquad H_{a_4}$$

5.1.4.1 Design of experiments

In the instance of the parameter team-size (n), the analysis similarly structures a design of experiments to examine its relationship, if any, to the productivity of the DAU, a function of the average fitness values of design-teams $(\overline{f_t})$ and total search-times (t_s). The corresponding experiment examines the result over multiple levels of design complexity. The design of experiments and simulation setup for the discussed results, as done in subsequent hypotheses, follows below in Table 5.30 and Table 5.31. This experimental setup results in 1,800 simulations.

Table 5.30 Behavior Space Implementation in Simulation for Hypothesis 4: Ideal Team-Size

mdt	["max-downtime" 40]	S	[“smoothness” [0 20 100]]
p	["prob_of_newcomer" 50]	Seed	["seed" random]
q	["prop_to_repeat" 85]	Repetitions	25
Team-size	[“team-size” [2 1 13]]	Stop After	150 ticks
		Commands	Setup, Go, Repeat

Table 5.31 Default Parameter Settings for Runs for Hypothesis 4: Ideal Team-Size

Fitness Goal	99.9%
Default Modelling Dynamics (Age?, Max-Downtime?, Hill-Climbing?, and Coalesce?)	On
Require Same Stopping Point Strategy (Consensus)	Off
Dynamic Diversity (Saw-Tooth Profile) Strategy	Off
Stop Diversity if Average of the DAU is Fit Strategy	Off
Pause and Restart Diversity Strategy	Off
Stop Prolonged Decision Making Strategy	On
Initial Management Pressure	1.0 dmnl
Allowable Diversity at Start	50

5.1.4.2 Testing Methodology

As before, the analysis begins by performing an ANOVA to ensure that there exists a statistically significant underlying relationship in the data relevant to the hypothesis under inspection. Specifically, the analysis uses the parameter team-size (n) as an input in testing for statistically significant relationships, specifically with respect to the productivity of the DAU. The analysis repeats these tests for each of the various levels of the design-landscape smoothness (S). Analysis of productivity includes both the average productivity and the marginal productivity of design. The analysis measures the average design productivity in terms of the total output relative to the total input, where the output corresponds to the average DAU fitness values ($\overline{f_t}$) and the input corresponds to the total designer-time used as measured by the number of designers (n) multiplied by the overall search-time (t_s). Similarly, the analysis computes marginal product as the change of the average fitness ($\overline{f_t}$) of the DAU relative to the total designer-time for a given incremental change to the number of designers on the design-team. When computing values are used in the calculations, such as the productivity, the analysis adopts the median values from each of the simulation repetitions.

Finally, in order to determine whether a maximum team-size exists and, if it does, what value it possesses, the analysis plots the marginal productivity to the various team-sizes for multiple design-landscapes of differing design complexity, as measured inversely by the design-landscape smoothness (S). The analysis further validates the statistical significance found in the ANOVA by testing for an association and correlation between the team-size and marginal productivity; this approach lets the analysis further test the portion of the hypothesis that states increasing team-sizes above the maximum team-size results in a loss in marginal productivity. Specifically the analysis includes a Spearman rank-order correlation for this purpose. This nonparametric test considers the strength and directionality of changes in the productivity of the DAU for changes to its team-size.

5.1.4.3 Results and Observations

The statistical test reveals that the marginal productivity and team-size remain statistically related and negatively correlated. The summary results of this initial test follow in Table 5.31. The tests for each level of smoothness and team-sizes are included in Appendix W. Figure 5.3 and Figure 5.4 depict the resulting maximum team-sizes for given levels of design complexity.

Table 5.32 Significance and Hypothesis Test for Hypothesis 4

Null Hypothesis	Test	Stat.	Decision [a b c d]
The mean differences among the means of marginal design productivity values for different values of n is 0.	ANOVA F-test	0.000 [c] Sig.	Reject the null hypothesis.
The relationship between n and the marginal productivity of the DAU is not negatively correlated.	Spearman's Rho	-0.646 [d]	

a. Asymptotic significances are displayed. The hypothesis test uses an alpha of 0.05.
b. Reject the null hypothesis for all Smoothness levels
c. Observed power for each test equaled 1.0
d. Correlation is significant at the 0.01 level (2-tailed)

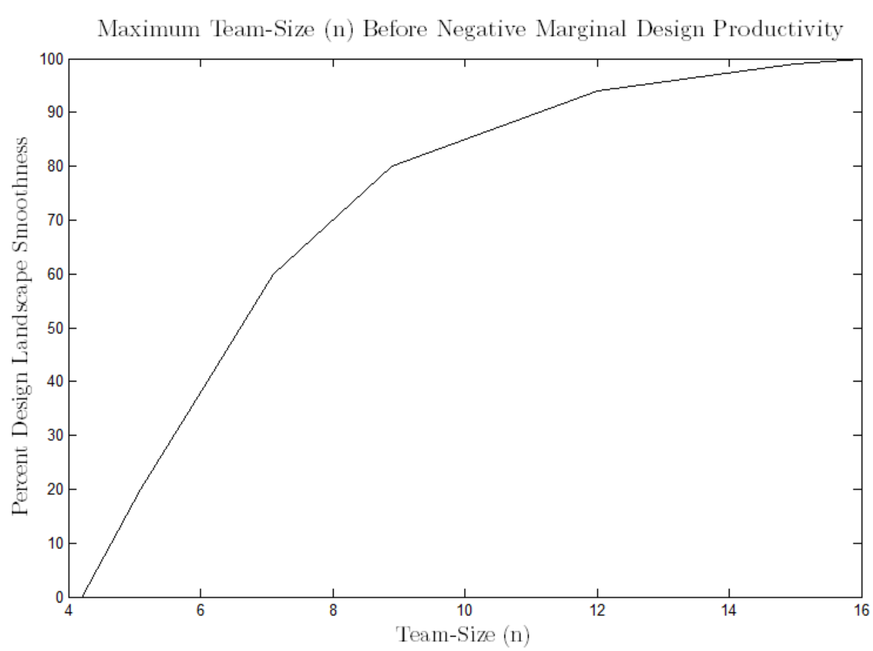


Figure 5.3 Maximum Team-Size with Landscape Smoothness Interpolation and Extrapolation

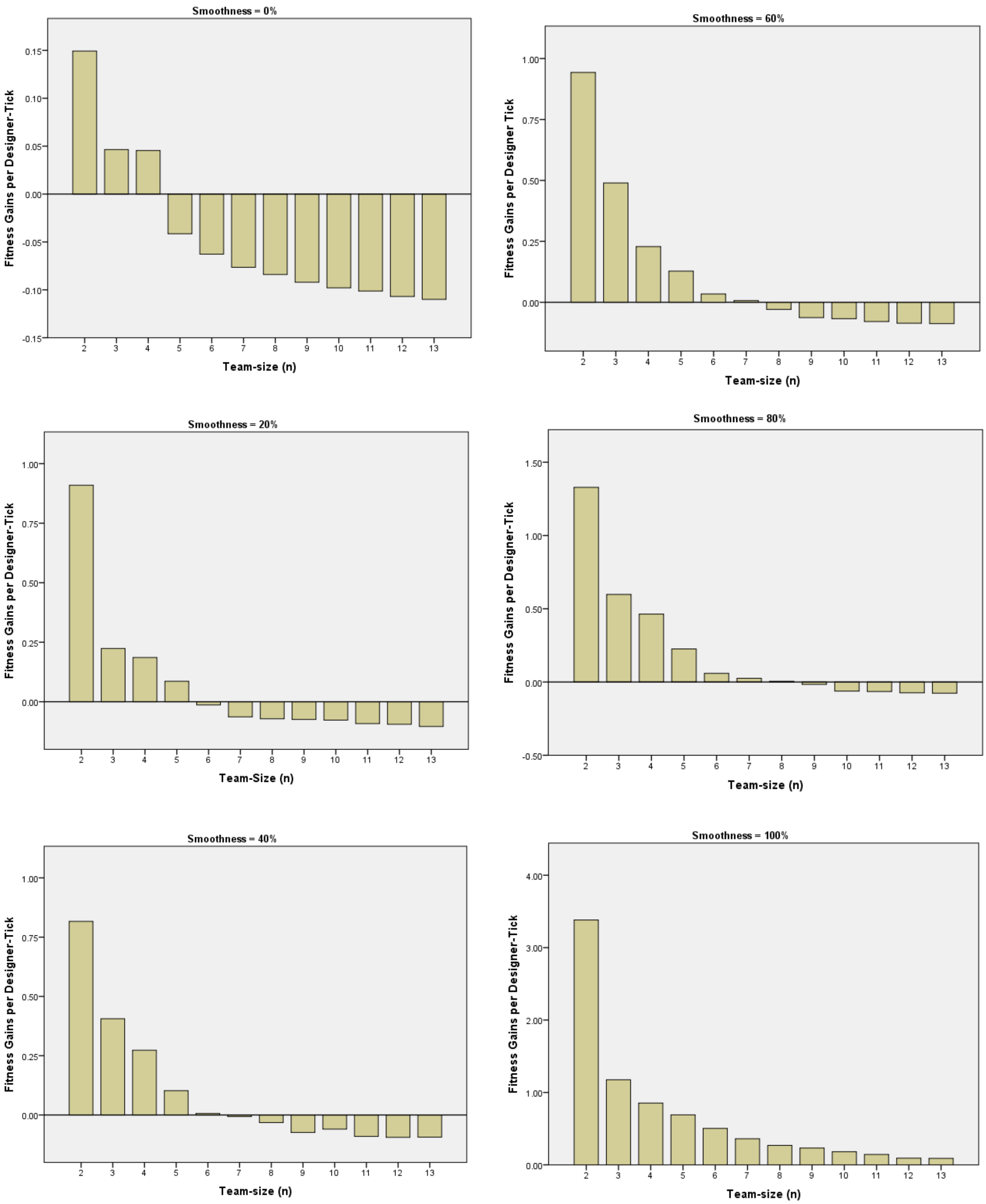


Figure 5.4 Summary of Marginal Design Productivity to Increases of Team-Size

Table 5.33 Team-size (n) Discussion and Complexity

Design Complexity	Max Size	Ideal Team Size for Design Productivity and Team Description
High Complexity	4	Minimally sized teams of $n = 4$ are ideal for highly complex tasks and are more than three times as productive as larger teams of $n = 10$ designers. Designers must work closely with one another to coordinate their actions; in the work environment, this closeness allows for communication that is more effective and requires each member to remain highly accountable to one another, in turn allowing for less formal and more adaptable roles. This adaptability allows for more efficient discovery and exploration of alternative design concepts.
Moderate Complexity	5	Small teams of $n = 5$ are ideal for moderately complex tasks. These design-teams have somewhat less cognitive demands placed on them from the design problem when compared to the highly complex design landscapes above. This reduction in cognitive toll provides the capacity for these teams to add an additional productive design-member over design-teams on highly complex design landscape. These design-teams preserve the agility and closeness of a small team while still only requiring minimal processes for coordination.
Average Complexity	7	Standard sized teams of $n = 6 - 7$ are ideal for tasks of average complexity. These design-teams begin to benefit from roles that are more formal, structured communication methods, and clear processes. Viewpoints of newcomers play, although still important, play a diminished role, *i.e.* diverse viewpoints are less significant.
Mild Complexity	8	Medium sized teams of $n = 7 - 8$ are ideal for tasks of limited complexity. These design-teams benefit more from increasingly formalized roles, communication methods, and processes. Technical leadership and management becomes increasingly important for group consensus at this size. These teams often suffer from groupthink overcoming the diverse viewpoints of newcomers, *i.e.* diverse viewpoints generally fade and design fixation becomes more common.
No Complexity	15	Large teams of $n = 10$ are ideal given an absence of design complexity; in these cases, the design-team can scale to a size of $n = 15$. Structured roles and routine processes allow these teams success in reaching design objectives. Additional designers in these situations improve the total design productivity; however, assuming any reasonable cost with respect to the addition of a new designer, the coordination challenges begin to make the almost negligible marginal gains for teams above of $n = 10$ questionable (and within the margin of error). In the real world, these small marginal gains for $n > 10$ likely stem from the likelihood of social loafing. Further, teams greater than $n = 10$ result in the natural subdivision into sub-teams.

Interestingly, the simulation results confirm that an ideal maximum for the size of a design-team does exist. However, the analysis also reveals an important nuance that the ideal maximum team-size, one where the team realizes all possible marginal benefits to productivity, remains highly sui generis to the level of complexity for a given design landscape. The results from the analysis for highly to moderately complex tasks, which require intense interactions due to the coupling of design decisions, small teams operate more efficiently. Table 5.33 captures some of the insights generated and Chapter 6 expands on possible policy recommendations.

However, even small teams of high-performing engineers and scientists may still be unable to design, build, test, and put a complicated and complex product (i.e. a large design landscape size N with a high degree of coupling K) in the marketplace fast enough to remain competitive. The previous discussion specifically addressed multiple levels of complexity without the size of the landscape. However, after further analysis (cf. Appendix AE), it is clear that the size of the design landscape in the C^2D model also has an impact on the productivity measures used. Although left primarily for future research, for projects requiring large teams the subdivision of these large teams into multiple teams across the various complexity levels generally follows the relationships described in Table 5.33 above. In other words, making large teams work like small teams requires a rational division of labor matched to the classification of complexity for each of the team subdivisions. These general relationships also held over multiple parameterization of team-formation parameters. Future research is required to better define the role of the newcomer probability (p) and the likelihood of repeating collaborations (q) parameters to these trends.

5.1.5 Hypothesis 5 – Newcomers and Performance

As found in Hypothesis 1, the probability of incorporating a newcomer (p) demonstrated a statistically significant relationship to the search-times (t_s) and average design-fitness values ($\overline{f_t}$) for the DAU. However, the exact relationship between these variables remained unaddressed. Here the research determines if in fact there is a positive linear correlation (R) between incorporating a newcomer and the search-times and average design-fitness values. Motivating this test is the larger research question of determining the relationship between newcomers and performance, with the goal of enabling the DAU management system to develop policies to minimize search-times while still achieving design objectives as discussed in Chapter 6. The analysis tests for this relationship as part of the corresponding hypothesis:

Alternative Hypothesis 5: There is a statistically significant positive linear correlation between the fraction of newcomers (p) and both the search-time (t_s) and average design-fitness values ($\overline{f_t}$).

$$t_s = \lambda p + \varepsilon \;\wedge\; \overline{f_t} = \lambda p + \varepsilon \quad \lambda, \varepsilon = \text{constant scalars} \qquad H_{a_5}$$

Null Hypothesis 5: There is not a statistically significant positive linear correlation between the fraction of newcomers (p) and both the search-time (t_s) and average design-fitness values ($\overline{f_t}$).

$$t_s \neq \lambda p + \varepsilon \;\wedge\; \overline{f_t} \neq \lambda p + \varepsilon \quad \lambda, \varepsilon = \text{constant scalars} \qquad H_{o_5}$$

5.1.5.1 DESIGN OF EXPERIMENTS

The design of experiments setup adopts the same experimental setup as from Hypothesis 1 and reuses the previously collected data. Table 5.34 and Table 5.35 summarize the original experimental setup. The experimental setup results in 2,600 simulations.

Table 5.34 Default Parameter Settings for Runs for Hypothesis 5

Smoothness (N=13, K=6)	50%
Allowable Diversity (m) at Start	50 patches
Fitness Goal	92%
Default Modelling Dynamics (Age?, Max-Downtime?, Hill-Climbing?, and Coalesce?)	On
Require Same Stopping Point Strategy (Consensus)	Off
Dynamic Diversity (Saw-Tooth Profile) Strategy	Off
Stop Diversity if Average of the DAU is Fit Strategy	Off
Pause and Restart Diversity Strategy	Off
Stop Prolonged Decision Making Strategy	Off
Initial Management Pressure	1.0 dmnl
Team-size (n)	4 ADMUs
Propensity to Repeat a Collaboration (q)	85%
Maximum-Downtime (mdt)*	40 ticks

Table 5.35 Behavior Space Implementation in Simulation for Hypothesis 5

p	["prob_of_newcomer" [20 5 80]]	Repetitions	100
Seed	["seed" random]	Commands	Setup, Go, Repeat
S	[“smoothness” 10 50]		

5.1.5.2 Testing Methodology

The analysis again uses a one-way ANOVA using multiple models to determine the trend (e.g. linear, quadratic) and its relative significance. The ANOVA allows the comparison of the dependent variables of final fitness values $\overline{f_t}$ and t_s to the different values of the probability to incorporate a newcomer p. Using this determination, the analysis then plots the means of the data and performs an appropriate regression of the data. This regression allows the analysis to observe the relative strength of the correlation and its direction (i.e. negative or positive correlations).

5.1.5.3 Results and Observations

The initial trend analysis supports the research hypothesis that there is a linear trend, as shown in Table 5.36. As before, the analysis examines the deviation term for significance to check for a higher ordered trend, which is not statistically present based on the observations. With this in hand, the analysis proceeds to fit the data with a linear regression as seen in Table 5.37 and Figure 5.5.

Table 5.36 Trend Analysis and One Way Analysis of Variance with p for Hypothesis 5

ANOVA for t_s			Sum of Squares	df	Mean Square	F	Sig.
Between Groups	(Combined)		1530474.422	12	127539.535	1.895	.031
	Linear Term	Contrast	619055.290	1	619055.290	9.197	.002
		Deviation	911419.132	11	82856.285	1.231	.260
	Quadratic Term	Contrast	12737.875	1	12737.875	.189	.664
		Deviation	898681.257	10	89868.126	1.335	.205
	Cubic Term	Contrast	10428.423	1	10428.423	.155	.694
		Deviation	888252.834	9	98694.759	1.466	.155
Within Groups			174129057.000	2587	67309.261		
Total			175659531.422	2599			

ANOVA for $\overline{f_t}$			Sum of Squares	df	Mean Square	F	Sig.
Between Groups	(Combined)		2078.661	12	173.222	6.350	.000
	Linear Term	Contrast	1957.704	1	1957.704	71.767	.000
		Deviation	120.957	11	10.996	.403	.955
	Quadratic Term	Contrast	2.419	1	2.419	.089	.766
		Deviation	118.538	10	11.854	.435	.930
	Cubic Term	Contrast	49.447	1	49.447	1.813	.178
		Deviation	69.091	9	7.677	.281	.980
Within Groups			70569.330	2587	27.278		
Total			72647.991	2599			

Table 5.37 Correlations in the Data for Hypothesis 5

R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
				R Square Change	F Change	df1	df2	Sig. F Change	
.289[a]	.084	.083	248.94068	.084	118.761	2	2597	.000	1.928

a. Predictors: (Constant), S, p

b. Dependent Variable: t_s

R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
				R Square Change	F Change	df1	df2	Sig. F Change	
.325[a]	.106	.105	5.00127	.106	153.724	2	2597	.000	1.829

a. Predictors: (Constant), S, p

b. Dependent Variable: $\overline{f_t}$

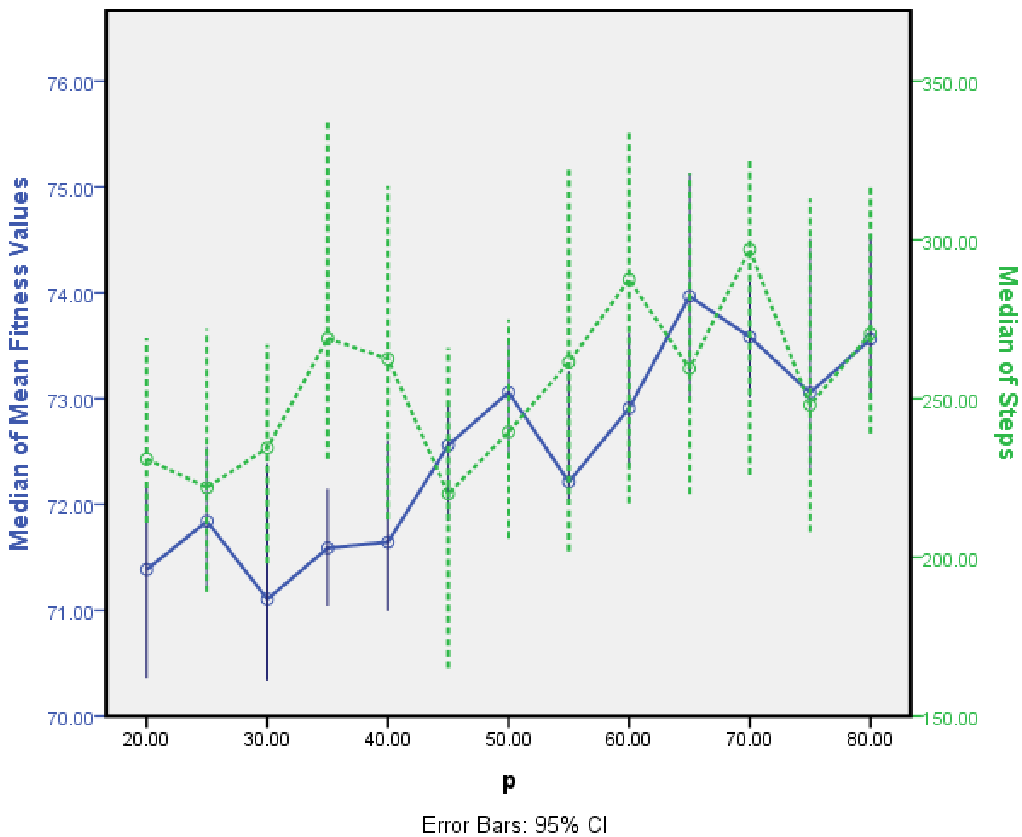


Figure 5.5 Plot of Medians for Design Search-Times and Average Design-Team Fitness Value for Hypothesis 5

Table 5.38 Significance and Hypothesis Test for Hypothesis 5

Null Hypothesis	Test	Stat.	Decision [a b c]
The mean difference among the means of t_s for different values of p is 0.	ANOVA F-test [a]	0.000 [b] Sig.	Reject the null hypothesis.
The mean difference among the means of $\overline{f_t}$ for different values of p is 0.	ANOVA F-test [a]	0.000 [b] Sig.	
The relationship between p and t_s is not positively correlated.	Pearson's R	0.289 [c]	
The relationship between p and $\overline{f_t}$ is not positively correlated.	Pearson's R	0.325 [c]	

a. Asymptotic significances are displayed. The hypothesis test uses an alpha of 0.05.
b. Observed power for each test using between subject effects equaled 1.0 for $\overline{f_t}$ and 0.937 for t_s
c. Correlation is significant at the 0.01 level (2-tailed)

The results suggest that incorporating newcomers does in fact raise the overall average design-team fitness values, as well as the overall search-times for these teams. However, a more important consideration for its implication to policy recommendations stems from what the overall relationship of the willingness of the team to incorporate newcomers has on the average productivity for the DAU. As seen in part with Hypothesis 2, the relationship between incorporating newcomers and the final performance of a design team remains complicated by other confounding variables, such as the propensity to repeat collaborations, the complexity of the design tasks, and, perhaps most importantly, the maximum allowable diversity for newcomers. An initial look at the results suggest, with significance at the 0.05 level (2-tailed) level using Spearman's Rho and Kendall's Tau b, that the average productivity of the design-team (i.e. the average design-team fitness by the designer-ticks) is very weakly and negatively correlated with the likelihood of incorporating a newcomer. However, by ensuring that there is enough allowable diversity, such as the allowance for cross-disciplinary specialists, into new design-teams approximately 30%-50% of newcomers in the design-team emerge from the data (cf. Appendix X) as an ideal range for structuring design-teams. Similarly, the research also considers the role of incumbency as an avenue for similarly improving the overall productivity of the DAU in the following hypothesis.

5.1.6 *Hypothesis 6 – The Known-Quantity*

The following hypothesis pursues a similar research goal as the one posed above, *i.e.* determining underlying relationships between the performance characteristics of the DAU and the propensity to repeat a collaboration (q). Another words, does the design-team favoring the selection of a known-quantity, *i.e.* an incumbents previously worked with, work to increase the efficiency of the DAU? From Hypothesis 1 the analysis found a statistical significance between the performance variables of interest, specifically the average design-team fitness ($\overline{f_t}$) and the search-time for the design-team (t_s), when the simulation required consensus from the DAU. However, as before, the exact relationship remained undetermined. As such, the following hypothesis explores the presence, if any, of a correlation in the data. Contrary to the previous hypothesis, the analysis tests specifically for a negative correlation and given nonlinearities expected with its response, the analysis does not presume any specific trend in the data (i.e. there may be logistical or higher order trends as to when the known-quantity benefits or hurts the DAU performance). The intuition underlying the assumption of a negative correlation is that as the team grows increasingly cohesive, which relates to increased repeated collaborations, the team will explore less of the design landscape and in turn complete its search more quickly at the expense of average design-team fitness. The following hypothesis explores the statistical significance of any negative correlation using the nonparametric Pearson's coefficient between the ranked variables (i.e. the Spearman correlation coefficient):

Alternative Hypothesis 6: There is a statistically significant negative correlation, using the Spearman correlation coefficient (ρ), between the propensity of a design-team to repeat a collaboration (q) and the average design-team fitness ($\overline{f_t}$), as well as search-times(t_s).

$$\rho = 1 - \frac{6\sum\left(q_i - \overline{f}_{t_i}\right)^2}{n(n^2-1)} < 0 \quad \wedge \quad \rho = 1 - \frac{6\sum\left(q_i - t_{s_i}\right)^2}{n(n^2-1)} < 0 \qquad q_i, f_{t_i}, t_{s_i} = ranks \qquad H_{a_6}$$

Null Hypothesis 6: There is not a statistically significant negative correlation, using the Spearman correlation coefficient (ρ), between the propensity of a design-team to repeat a collaboration (q) and the average design-team fitness ($\overline{f_t}$), as well as search-times (t_s).

$$\rho = 1 - \frac{6\sum\left(q_i - \overline{f}_{t_i}\right)^2}{n(n^2-1)} = 0 \quad \wedge \quad \rho = 1 - \frac{6\sum\left(q_i - t_{s_i}\right)^2}{n(n^2-1)} = 0 \qquad q_i, f_{t_i}, t_{s_i} = ranks \qquad H_{o_6}$$

5.1.6.1 Design of experiments

The research replicates the design of experiments from Hypothesis 1 for the propensity to repeat a collaboration (q). The analysis structures the range for the test to reflect the likely values for the DAU based on observations from Guimerà et al. (2005) in other creative and scientific collaboration types. As before, the analysis enforces the need for consensus in decision-making as part of the analysis given the previous findings from Hypothesis 1. The overall setup follows below in Table 5.39 and Table 5.40. This experimental setup requires 620 simulations.

Table 5.39 Behavior Space Implementation in Simulation for Hypothesis 6

q	["prop_to_repeat" [70 1 100]]
Seed	["seed" random]
S	[“smoothness” 10 50]
Repetitions	10
Commands	Consensus, Setup, Go, Repeat

Table 5.40 Default Parameter Settings for Runs for Hypothesis 6

Smoothness (N=13, K=6)	50%
Allowable Diversity (m) at Start	50 patches
Fitness Goal	92%
Default Modelling Dynamics (Age?, Max-Downtime?, Hill-Climbing?, and Coalesce?)	On
Require Same Stopping Point Strategy (Consensus)	On
Dynamic Diversity (Saw-Tooth Profile) Strategy	Off
Stop Diversity if Average of the DAU is Fit Strategy	Off
Pause and Restart Diversity Strategy	Off
Stop Prolonged Decision Making Strategy	Off
Initial Management Pressure	1.0 dmnl
Team-size (n)	4 ADMUs
Propensity to Repeat a Collaboration (q)	85%
Maximum-Downtime (mdt)*	40 ticks

5.1.6.2 Testing Methodology

Given the expected nonlinearity in the relationship between the q parameter and the performance variables, the analysis uses a series of bivariate nonparametric tests to determine correlations and their relative strengths. Primarily, this includes using the Spearman’s rank correlation coefficient seen in the hypothesis statement. This rank measure determines the statistical dependence between two variables based on the monotonicity of their relationship, *i.e.* a measure of how often a change in the independent variable in one direction (i.e. positive) corresponds to a change in the direction of the dependent variable (i.e. negative or positive). Similarly, the analysis confirms that a dependent relationship exists and its direction by similarly employing another nonparametric test, the Kendall rank correlation coefficient statistic (Kendall 1938; Sen 1968). This τ_b test similarly uses a measure of rank correlation; it also includes the similarity of the orderings of the data and differs from other Kendall rank tests by adjusting the data for ties as specified by Ntzoufras (2011).

5.1.6.3 Results and Observations

The statistical tests and findings follow in Table 5.41 and Table 5.42 respectively. The findings suggest that there is in fact a weak negative correlation between the propensity to repeat a collaboration (q) and the average design-team fitness ($\overline{f_t}$) and search-time (t_s).

Table 5.41 Nonparametric Correlations for Hypothesis 6

			$\overline{f_t}$	t_s
Kendall's Tau-B (τ_b)	q	Correlation Coefficient	-.099**	-.098**
		Sig. (2-tailed)	.001	.001
		N	540	540
	$\overline{f_t}$	Correlation Coefficient	1.000	.305**
		Sig. (2-tailed)	.	.000
		N	540	540
	t_s	Correlation Coefficient	.305**	1.000
		Sig. (2-tailed)	.000	.
		N	540	540
Spearman's Rho (ρ)	q	Correlation Coefficient	-.148**	-.137**
		Sig. (2-tailed)	.001	.001
		N	540	540
	$\overline{f_t}$	Correlation Coefficient	1.000	.430**
		Sig. (2-tailed)	.	.000
		N	540	540
	t_s	Correlation Coefficient	.430**	1.000
		Sig. (2-tailed)	.000	.
		N	540	540

**. Correlation is significant at the 0.01 level (2-tailed).

Table 5.42 Significance and Hypothesis Test for Propensity to Repeat a Collaboration

Null Hypothesis	Test	Corr. Coeff.	Decision [a b c d e]
The correlation between q and $\overline{f_t}$ is not negative and equals 0.	Spearman's Rho	-.148 [d e]	Reject the null hypothesis for tested range.
The correlation between q and t_s is not negative and equals 0.	Spearman's Rho	-.137 [d e]	Reject the null hypothesis for tested range.

a. Reject the null hypothesis only for the given range tested for q between 70 and 85%.
b. Significance only found when consensus in the simulation was required.
c. Tests of between-subjects effects (Appendix S) demonstrates an observed power of 1.0 for each.
d. Correlation is significant at the 0.01 level (2-tailed).
e. Sign test and Wilcoxon Signed Ranks Test each have asymp. sig. (2-tailed) of .000.

Despite the weak correlation in the data, the analysis did nevertheless reveal a statistically significant relationship between the average fitness of the design team and the search-times of the design team when examined over a particular range for the propensity to repeat a collaboration. This examined range corresponds to the likely ranges for the likelihood designers in a DAU would repeat their collaborations based on its correlation to the literature and findings from Guimerà et al. (2005) discussed in Chapter 2. From any analytical perspective, this means that the benefits of having a team of well-established and repeated relationships may offer only a marginal benefit (based on the strength of the correlation) to search-times. These findings remain balanced against the benefits of other parameters, including their relative strengths, when developing a larger and more holistic design-team structure and design management strategy. Consequently, the data has important policy implications for the DAU as summarized in Chapter 6. The research continues with a discussion of the effects of particular design strategies and their influence on the ability of a design team to perform.

5.1.7 Hypothesis 7 - Continuous Diversity Management

Given the preceding hypotheses, concerning the role of the newcomer and diversity, the research now considers the possibility of creating rules, *i.e.* strategies, by which the DAU can operate to improve its design outcomes and performance. In the empirical world, finding the right balance of diversity remains elusive; further, the simulations performed demonstrate that the beneficial correlations between improved performance and an increase in diversity typically lag one another. The research considers a strategy that allows the DAU to benefit from diversity while limiting its exposure to overly dramatic swings in performance, specifically the introduction of radically new development approaches that may determinately affect the design time. In other words, the research investigates a strategy of starting with evolutionary exploration prior to considering radical innovations. The proposed continuous diversity management strategy includes gradually casting a net wider and wider in terms of diversity for its new talent. However, after casting the widest possible net, *i.e.* once all relevant skills sets to the design feasibility space have had been considered (the maximum distance from any point to another on the design landscape has been considered), the DAU temporarily halts the inclusion of new concepts to pursue and focus on its recently discovered feasible solution set. If any of these new ideas are successful, it focuses on developing them. However, if none of the ideas satisfice design thresholds the process repeats. From a modelling perspective, this pattern of search results in a saw wave function for diversity, *i.e.*, the allowable diversity ramps until the DAU reaches a sufficiently fit design concept or it meets the maximum diversity threshold. At this point the DAU collaboration reorients itself and assesses its state; it does this by temporarily setting diversity to zero. This temporary reprieve from a growing number of competing ideas and concepts, which constantly tug at the conceptual center of the DAU, allows the DAU to sift through recently discovered potential approaches and find concepts worth pursuing further. If the average during this search ever reaches a sufficiently fit design solution, the strategy similarly hones in on that design solution by stopping diversity and only bringing in the most relevant skillsets. The corresponding hypothesis follows:[42]

Alternative Hypothesis 7: Varying the diversity of newcomers (m) to the design-team at each unit of time, using a saw-tooth wave function, when unfit improves search-times (t_s) and the design-team final fitness values (f_t).

$$f_t|_{m(t)=t-\lfloor t \rfloor} > f_t|_m \quad \wedge \quad t_s|_{m(t)=t-\lfloor t \rfloor} < t_s|_m \qquad H_{a_7}$$

Null Hypothesis 7: Varying the diversity of newcomers (m) to the design-team at each unit of time, using a saw-tooth wave function, when unfit neither improves search-times (t_s) nor the design-team final fitness values (f_t).

$$f_t|_{m(t)=t-\lfloor t \rfloor} \ngtr f_t|_m \quad \wedge \quad t_s|_{m(t)=t-\lfloor t \rfloor} \nless t_s|_m \qquad H_{o_7}$$

[42] Hypothesis 10 by comparison discusses the possibility of limiting the strategy to ceasing diversity upon discovery of a fit solution, as opposed to actually increasing or decreasing the level of allowable diversity over time.

5.1.7.1 Design of experiments

The research again structures a design of experiments to examine the final fitness values of design-teams (f_t) and their search-times(t_s) for the strategy enabled and disabled. From Chapter 3, the strategy relies on the pause and restart dynamic, the use of dynamic increasing diversity, and stopping diversity of the DAU after it finds a fit solution. In addition, this experimental setup includes multiple parameterizations. The design of experiments follows a similar setup as used earlier, and follows below in Table 5.43 and Table 5.44. This experimental setup results in 1,200 simulations.

Table 5.43 Behavior Space Implementation in Simulation for Hypothesis 7

n	["team-size" 4 5 6]	Seed	["seed" random]
p	["prob_of_newcomer" 50 85]	Repetitions	50
q	["prop_to_repeat" 50 85]	Strategy	[“diversity strategy” true false]
S	["smoothness" 50 80]	Commands	Setup, Go, Repeat

Table 5.44 Default Parameter Settings for Runs for Hypothesis 7

	Allowable Diversity (m) at Start	50 patches
	Fitness Goal	92%
	Default Modelling Dynamics (Age?, Max-Downtime?, Hill-Climbing?, and Coalesce?)	On
	Require Same Stopping Point Strategy (Consensus)	On
Continuous Diversity Management Strategy	Pause and Restart Diversity Strategy	On*
	Dynamic Diversity Strategy	
	Stop Diversity if Average of the DAU is Fit Strategy	
	Stop Prolonged Decision Making Strategy	Off
	Initial Management Pressure	1.0 dmnl
	Team-size (n)	4 ADMUs
	Propensity to Repeat a Collaboration (q)	85%
	Maximum-Downtime (mdt)*	40 ticks

** Turned on and off as a group per main hypothesis objective.*

5.1.7.2 Testing Methodology

As done in previous tests, the analysis performs a between-factors analysis of variables using an analysis of variance (ANOVA) to determine statistical significance. Additionally, the analysis compares the data in two groupings (one with the strategy applied and one without the application the strategy applied) by splitting the data file into corresponding sets based on the strategy state (i.e. on or off). The analysis also uses a Wilcoxon rank comparison of these data sets to verify any significance detected as part of the original ANOVA. In addition, the research captures the descriptive statistics for the comparison of the with- and without-strategy groups. Finally, the analysis runs a bivariate correlation to capture the strengths of any relationship to support further any statistical finding.

5.1.7.3 Results and Observations

The summary of between subject effects captured as part of the ANOVA follows in Table 5.45. This table finds significance between the Diversity Management Strategy employed and the resulting final fitness values (f_t), maximum fitness values obtained ($max\ f_t$), average fitness values ($\overline{f_t}$), and the total search-times for the DAU. After splitting the data into different treatment groups, the summary statistics for these groups follow in Table 5.46 and Figure 5.6. A Wilcoxon Sign Ranked Tests confirms the statistical significance of these two different groups. Additionally, the analysis includes these test results as well as the full summary table of effects in Appendix Y. Additionally, the overall statistical findings follow as part of Table 5.47.

Table 5.45 Summary of Between Subject Effects ANOVA for Hypothesis 7

Source	Dependent Variable	Type III Sum of Squares	Df	Mean Square	F (1,1018)	Sig.	Noncent. Parameter	Obs. Power[a]
Diversity Management Strategy	f_t	6702.733	1	6702.733	223.869	.000	223.869	1.000
	$max(f_t)$	2619.272	1	2619.272	119.744	.000	119.744	1.000
	$\overline{f_t}$	170.492	1	170.492	8.355	.004	8.355	.824
	t_s	17765331.398	1	17765331.398	182.219	.000	182.219	1.000

a. Observed Power ($1-\beta$) computed using alpha = .05

Table 5.46 Comparison of Descriptive Statistics with Strategy for Hypothesis 7

Grand Mean					
Diversity Management Strategy	Dependent Variable	Mean	Std. Error	95% Confidence Interval	
				Lower Bound	Upper Bound
Strategy Off	f_t	77.956[a]	.216	77.532	78.379
	$max(f_t)$	79.155[a]	.174	78.813	79.496
	$\overline{f_t}$	70.692[a]	.223	70.255	71.129
	t_s	379.871[a]	14.336	351.755	407.988
	$PI = f_t/t_s$	2.762[a]	.223	2.325	3.199
Strategy On	f_t	80.015[a]	.107	79.804	80.226
	$max(f_t)$	80.360[a]	.107	80.150	80.569
	$\overline{f_t}$	70.673[a]	.152	70.375	70.972
	t_s	261.987[a]	6.967	248.325	275.649
	$PI = f_t/t_s$	2.904[a]	.122	2.665	3.143

a. Based on modified population marginal mean.

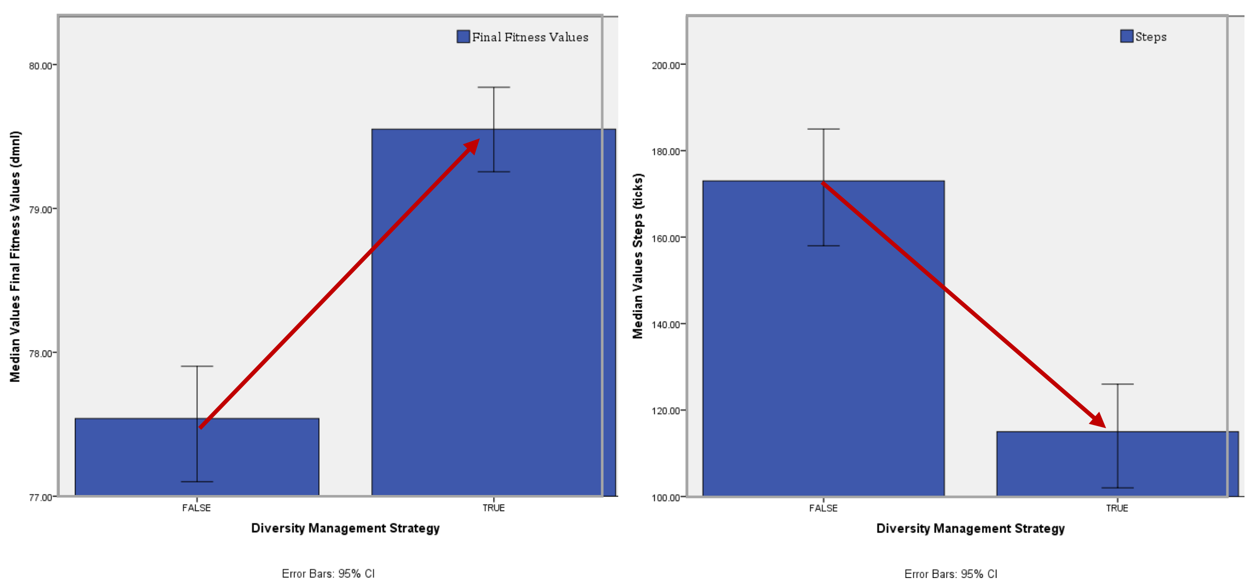


Figure 5.6 Final Fitness (left) and Search-Times (right) with Strategy Application from Hypothesis 7

Table 5.47 Significance and Hypothesis Testing for Hypothesis 7

Null Hypothesis	Test	Stat.	Decision [a b c d e]
The mean difference among the means of f_t with the continuous diversity management strategy applied versus not applied is 0.	ANOVA F-test [a]	0.001 [a c] Sig.	Reject the null hypothesis.
The mean difference among the means of t_s with the continuous diversity management strategy applied versus not applied is 0.	ANOVA F-test [a]	0.000[a] Sig.	
The relationship between the continuous diversity management strategy and f_t as a percentage of the global fitness values is not correlated.	Pearson's R	0.275 [b c]	
The relationship between the continuous diversity management strategy and t_s is not correlated.	Pearson's R	-0.176 [b]	
The relationship between the continuous diversity management strategy and both the t_s and f_t is not correlated.	Wilcoxon (cf. Appendix X)	0.000 [d] Sig.	

a. Observed power for each test using between subject effects equaled 1.0 for f_t and 1.0 for t_s
b. Correlation is significant at the 0.01 level (2-tailed)
c. Use of raw final fitness values, instead of final fitness as a percent of the global maximum, results in a slightly lower correlation of 0.219
d. Correlation is significant at the 0.01 level (2-tailed) for both tests.
e. Asymptotic significances are displayed. The hypothesis test uses an alpha of 0.05.

These findings demonstrate the clear role of simple rules or strategies in the performance of a collaborative effort. Specifically, these findings demonstrate that the DAU can significantly improve its final fitness while also significantly reducing its search-times through a set of rules that actively manages the diversity of its teams. The success of these implementations depends heavily on the ability of the DAU to measure and understand diversity in the context of its application and the design landscape. Take the instance of the C^{2}D framework discussed where conceptual loci represent the patches on the design landscape and diversity represents distances between these loci, the translation of these concepts into measureable attributes for a management system remains essential to the implementation of any strategy. Although the particular implementations of these measures remain the subject of future research, a DAU management system could choose to measure these differences through readily understood similarity indices, such as the Jaccard Coefficient for Keywords Similarity discussed by Niwattanakul, Singthonchai, Naenudorn, and Wanapu (2013). For example, the DAU could measure the similarity of résumés when recruiting newcomers relative to the existing design-team and to the overall collaborative enterprise. Further, it could measure differences in design approaches by using a similar measures applied to design approaches and their technical performance measures (e.g. fitness differences).

The research provides the benefit of being able to test these design strategies and their variants. The strategy tested in Hypothesis 7 employs a simple set of rules whereby the design-team increases its diversity, *i.e.* acceptable degree of conceptual exploration, when the average of the DAU is unfit based on its current performance until it reaches a concept of sufficient fitness or it has exhausted the limits of design exploration (i.e. reached its maximum diversity level). Figure 5.7 highlights a typical DAU response to this strategy. At the beginning of the simulation, the DAU explores the landscape, when the average of the DAU locates a design concept of sufficient fitness the exploration stops and all of the competing design concepts undergo a period of exploitation and design consensus. However, if the design team fails to coalesce around one of the design concepts the DAU again promotes exploration. The failure to reach a final design can occur because of different design constituencies forming in the DAU over time; depending on their size (i.e. influence), unaligned constituencies often restrain the adaptability of the DAU to move to new solutions. Part of this overall restraint stems from the overall size of the collaboration. The next hypothesis examines maximum-downtime, which may help to alleviate an unnecessary overhang of DAU collaborators. Chapter 6 further highlights the policy implications of this strategy.

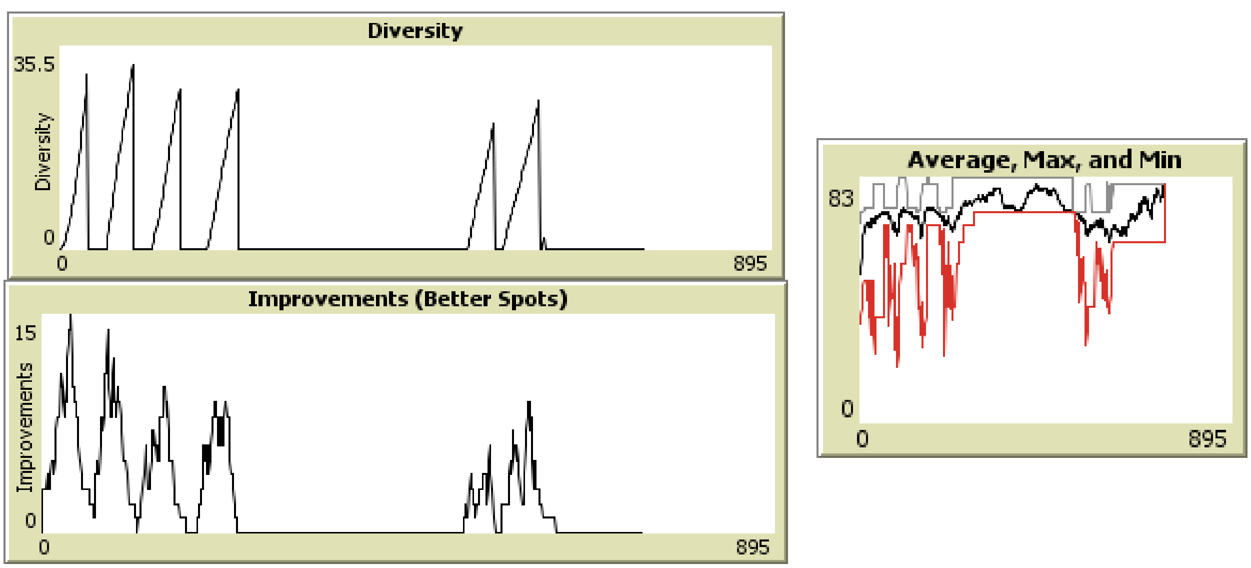


Figure 5.7 Continuous Diversity Management Example of DAU Response

5.1.8 *Hypothesis 8 – Maintaining the Talent Capacity*

The preceding hypotheses and simulation addressed the role of actively managing diversity. However, the analysis also discussed the potential for design constituencies (i.e. groups of designers with similar design preferences) to create inertia and degrade the ability of the DAU to adapt to new design alternatives. These design constituencies gain sway when new ideas, as advocated by their designers, do not receive adequate time to take hold. In the C^2D model, two factors influence the ability of agents (and their representative design positions) to leave: 1) the degree of selection pressure from management(λ_u) regarding the performance and fitness of designers and their concepts, and 2) the maximum-downtime (mdt) that a design collaborator will stay involved in a collaboration when unengaged prior to leaving the DAU. As part of these factors, this hypothesis explores in particular the maximum-downtime (mdt). In particular, the analysis examines the relationships and strength of this parameter in the ability for design concepts to take hold. By having fit design concepts take hold earlier on and gain momentum, the final design times should actually diminish. The test of significance of this relationship follows from Hypothesis 8.

Alternative Hypothesis 8: Increasing the *maximum-downtime* (mdt) decreases the search-time of the design-team (t_s).[43]

$$mdt \approx {}^{\lambda}/_{t_s} \qquad \lambda = \text{constant scalar} \qquad H_{a_8}$$

Null Hypothesis 8: Increasing the *maximum-downtime* (mdt) does not decrease the search-time of the design-team (t_s).

$$mdt \not\approx {}^{\lambda}/_{t_s} \qquad \lambda = \text{constant scalar} \qquad H_{o_8}$$

5.1.8.1 Design of experiments

The design of experiments examines the search-times(t_s) and, although outside the stated hypothesis, the final fitness values of design-teams (f_t) for different values of the maximum-downtime (mdt). The design of experiments follows a similar setup as used earlier, and follows below in Table 5.48 and Table 5.49. This experimental setup again results in 570 simulations.

[43] The maximum-downtime (mdt) equates to the allowable amount of time, measured in ticks, an agent of the larger collaboration can exist apart from the team without losing interest and leaving the collaboration.

Table 5.48 Behavior Space Implementation in Simulation for Hypothesis 8

n	["team-size" 4]	mdt	["max-downtime” [10 5 100]]
p	["prob_of_newcomer" 50]	Seed	["seed" random]
q	["prop_to_repeat" 85]	Repetitions	30
S	["smoothness” 20]	Commands	Setup, Go, Repeat

Table 5.49 Default Parameter Settings for Runs for Hypothesis 8

	Allowable Diversity (m) at Start	50 patches
	Fitness Goal	92%
	Default Modelling Dynamics (Age?, Max-Downtime?, Hill-Climbing?, and Coalesce?)	On
	Require Same Stopping Point Strategy (Consensus)	On
Continuous Diversity Management Strategy	Pause and Restart Diversity Strategy	On
	Dynamic Diversity Strategy	
	Stop Diversity if Average of the DAU is Fit Strategy	
	Stop Prolonged Decision Making Strategy	Off
	Initial Management Pressure	1.0 dmnl

5.1.8.2 Testing Methodology

The analysis relies on an ANOVA to test for between subject effects. In order to determine the correlations between the data, the analysis utilizes a linear regression to determine the Pearson’s R correlation value. Additionally, the analysis also makes use of the Spearman’s rank correlation coefficient seen earlier in Hypothesis 6.

5.1.8.3 Results and Observations

The summary of between subject effects captured as part of the ANOVA follows in Table 5.50, with the complete effects in Appendix Z. The ANOVA confirms the earlier analysis from Hypothesis 1 by finding a statistically significant relationship between the maximum-downtime (mdt) and the resulting final fitness values (f_t) and the total search-times (t_s) for the DAU. The analysis utilizes a linear regression model and bivariate correlation between factors model as seen in Table 5.51 and Table 5.52 respectively. The overall statistical findings follow as part of Table 5.53.

Table 5.50 Summary of Between Subject Effects ANOVA for Hypothesis 8

Source	Dep. Variable	Type III Sum of Squares	Df	Mean Square	F (1,569)	Sig.	Noncent. Parameter	Obs. Power[a]
mdt	f_t[b]	.041	18	.002	1.973	.010	35.509	.979
	t_s	1770812.425	18	98378.468	1.905	.014	34.286	.974

a. Observed Power $(1-\beta)$ computed using alpha = .05

b. Fitness values measured relative to the global maximum f_t.

Table 5.51 Pearson Correlation for Maximum-Downtime in Hypothesis 8

		mdt	t_s	f_t
mdt	Pearson Correlation	1	-.150**	.134**
	Sig. (2-tailed)		.000	.001
	Sum of Squares and Cross-products	427500.000	-538340.000	71.839
	Covariance	751.318	-946.116	.126
	N	570	570	570

**Correlation is significant at the 0.01 level (2-tailed).

Table 5.52 Spearman's Rho Correlation for Hypothesis 8

			mdt	t_s	f_t
Spearman's ρ	mdt	Correlation Coefficient	1.000	-.194**	.132**
		Sig. (2-tailed)	.	.000	.002
		N	570	570	570
	t_s	Correlation Coefficient	-.194**	1.000	-.193**
		Sig. (2-tailed)	.000	.	.000
		N	570	570	570
	f_t	Correlation Coefficient	.132**	-.193**	1.000
		Sig. (2-tailed)	.002	.000	.
		N	570	570	570

**. Correlation is significant at the 0.01 level (2-tailed).

Table 5.53 Significance and Hypothesis Testing for Hypothesis 8

Null Hypothesis	Test	Stat.	Decision [a b c]
The mean differences between the means of t_s for different values of mdt is 0.	ANOVA F-test [a]	0.000 [b] Sig.	Reject Null Hypothesis
The relationship between mdt and t_s is not negatively correlated.	Pearson's R	-0.150 [c]	
	Spearman's Rho (ρ)	-0.194 [c]	

a. Asymptotic significances are displayed. The hypothesis test uses an alpha of 0.05.
b. Observed power for each test using between subject effects equaled 0.974 for t_s
c. Correlation is significant at the 0.01 level (2-tailed)

The analysis reveals a statistically significant weak negative correlation between the maximum-downtime and the design search-times, and, although outside the original hypothesis, a statistically significant weak positive correlation to the final fitness values achieved for the DAU. In effect, this relationship suggests that encouraging designers to stay affiliated with a project for longer can improve the final search-times and final fitness values for a design effort. The maximum-downtime helps to regulate the support network of collaborative designers, *i.e.* the pool of talent potential available to the DAU. By encouraging this pool of potential to remain affiliated with a design project for longer, potentially meritorious ideas have longer to take hold, grow, and gain the approval of a larger percentage of the DAU. On the other extreme, without regulation if the DAU grows too large, performance quickly erodes any performance benefit. This has important policy implications; specifically this finding suggests that when regulating the DAU with respect to performance, better courses of action for improving the DAU performance come through improving the other regulating element of the DAU, through management and technical leadership. This management, a measure of the selectivity in discriminating solutions and providing resources, represents a core consideration in the following hypothesis.

5.1.9 Hypothesis 9 – Baseline Management Target

The selectivity of the DAU when choosing what design concepts to pursue and what design constituencies to support arises from the ability of the management-system, in particular the resource holder, of the DAU to influence the evolution of the design process. The research considers the degree of this influence as a relative measure of the management and technical leadership pressure (λ_u) exerted on the design collaborators during their exploration. In effect, this simulated parameter provides the strength of the underlying natural selection metaphor as discussed in Chapter 3 and as implemented in Chapter 4. As implemented, values under one for the parameter correspond to a lower threshold for minimum fitness values compared to the design fitness objective. In other words, a parameter value of zero corresponds to the management system never participating in the design process. Conversely, parameter values greater than one corresponds to increasing expectations of fitness greater than the fitness threshold. As this greater expectation occurs, a greater culling of agents occurs as the DAU management system sorts through the undesirable design options, leaving fitter design alternatives to remain in the design process. With this greater involvement, the impact to the number of designers and design concepts also logarithmically increases as seen in Figure 5.8. As the parameter increases, the DAU refines its pursuits to existing design concepts of increasingly higher fitness thresholds relative to its objective fitness (i.e. the stopping fitness). However, for meritorious design concepts that require a large amount of exploration (i.e. long adaptive walks), too much selectivity from the design management system from the very start of the design process may overly discount concepts too early on. As part of these considerations, the analysis considers the role of this parameter with respect to the search-times.

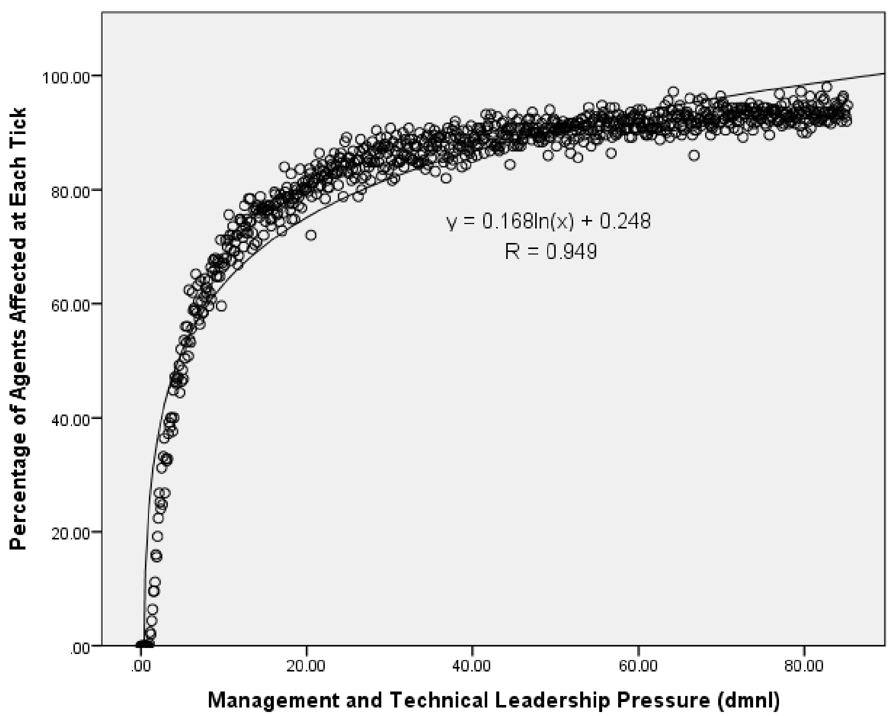


Figure 5.8 Percentage of Agents Influenced at Each Tick with λ_u Simulated with a Random Normal Distribution of Fitness for the Design Landscape

Specifically, the research poses the question of whether more oversight and increased selectivity of the DAU throughout the design process leads to a shortened design cycle and, if it does, over what range does this benefit occur? The research tests for this in the following the hypothesis:

Alternative Hypothesis 9: There is a statistically significant negative correlation, using the Spearman's correlation coefficient (ρ), between the management and technical leadership pressure (λ_u) and the search-time for the design-team (t_s).

$$\rho < 0 \qquad H_{a_9}$$

Null Hypothesis 9: There is not a statistically significant negative correlation, using the Spearman's correlation coefficient (ρ), between the management and technical leadership pressure (λ_u) and the search-time for the design-team (t_s).

$$\rho \geq 0 \qquad H_{o_9}$$

5.1.9.1 Design of experiments

The design of experiments examines the search-times (t_s) and, although outside the stated hypothesis, the final fitness values of design-teams (f_t) for different values of management and technical leadership pressure (λ_u). The design of experiments follows a similar setup as used in the previous hypothesis, and follows below in Table 5.54, Table 5.55, and Table 5.56. This experimental setup is ran twice, once over a large range and once over a smaller range, and results in 2,525 simulations and 510 simulations respectively.

Table 5.54 Behavior Space Implementation in Simulation 1 for Hypothesis 9

n	["team-size" 4]	λ_u	["management_pressure" [0 0.5 50]]
p	["prob_of_newcomer" 50]	Seed	["seed" random]
q	["prop_to_repeat" 85]	Repetitions	25
S	["smoothness" 20]	Commands	Setup, Go, Repeat

Table 5.55 Behavior Space Implementation in Simulation 2 for Hypothesis 9

n	["team-size" 4]	λ_u	["management_pressure" [0 0.05 2.5]]
p	["prob_of_newcomer" 50]	Seed	["seed" random]
q	["prop_to_repeat" 85]	Repetitions	10
S	["smoothness" 20]	Commands	Setup, Go, Repeat

Table 5.56 Default Parameter Settings for Runs for Hypothesis 9

<table>
<tr><td></td><td>Allowable Diversity (m) at Start</td><td>50 patches</td></tr>
<tr><td></td><td>Fitness Goal</td><td>92%</td></tr>
<tr><td></td><td>Default Modelling Dynamics
(Age?, Max-Downtime?, Hill-Climbing?, and Coalesce?)</td><td>On</td></tr>
<tr><td></td><td>Require Same Stopping Point Strategy
(Consensus)</td><td>On</td></tr>
<tr><td rowspan="3">Continuous Diversity Management Strategy</td><td>Pause and Restart Diversity Strategy</td><td rowspan="3">On</td></tr>
<tr><td>Dynamic Diversity Strategy</td></tr>
<tr><td>Stop Diversity if Average of the DAU is Fit Strategy</td></tr>
<tr><td></td><td>Stop Prolonged Decision Making Strategy</td><td>Off</td></tr>
<tr><td></td><td>Initial Management Pressure</td><td>1.0 dmnl</td></tr>
</table>

5.1.9.2 Testing Methodology

The testing relies on an ANOVA for capturing between subject effects and any significance. The analysis repeats this test for both range of the parameter used in the simulation as highlighted in Table 5.54 and Table 5.55 above. In order to determine the correlations between the data (including the direction of the correlation), the analysis again makes uses the Spearman's rank correlation.

5.1.9.3 Results and Observations

The ANOVA reveals a statistically significant relationship between the management and technical leadership pressure (λ_u) and the performance characteristics of the DAU, specifically the search-times (t_s) addressed in the hypothesis. Table 5.57 highlights the significance of these relationships for both the wide range of parameter values and for the targeted range of parameter values. The targeted range of parameter values corresponds to region of transition in the behavior of the model as seen in Figure 5.9. Similarly, the analysis calculates the Spearman's correlation coefficient between the parameter and performance variables in Table 5.58. This table similarly compares the two examined ranges for the strength of any of the statistically significant relationships. The relationships show that for the particular transition region of the DAU, the technical management and leadership pressure has a strong correlation both inversely with search-times and with the final design fitness values achieved by the DAU.

Table 5.57 Summary of Between Subject Effects ANOVA for Hypothesis 9

Wide Range of Values (0 to 50)	Source	Dep. Var.[e]	Type III Sum of Squares	df	Mean Square	F (100, 2424)	Sig.	Noncent. Param.	Obs. Power[a]
	λ_u	f_t	1.051[b]	100	.011	6.980	.000	698.026	1.000
		$\overline{f_t}$	.595[c]	100	.006	2.465	.000	246.522	1.000
		t_s	31107204.192[d]	100	311072.042	5.885	.000	588.498	1.000

a. Observed Power $(1-\beta)$ computed using alpha = .05
b. R Squared = .224 (Adjusted R Squared = .192) based on Corrected Model
c. R Squared = .092 (Adjusted R Squared = .055) based on Corrected Model
d. R Squared = .195 (Adjusted R Squared = .162) based on Corrected Model
e. Fitness measured relative to global max. fitness (f_m)

Narrow Range of Values (0 to 2.5)	Source	Dep. Var.[e]	Type III Sum of Squares	df	Mean Square	F (100, 459)	Sig.	Noncent. Param.	Obs. Power[a]
	λ_u	f_t	2.338[b]	50	.047	13.730	.000	686.478	1.000
		$\overline{f_t}$	.744[c]	50	.015	6.795	.000	339.769	1.000
		t_s	501097160.051[d]	50	10021943.2	106.985	.000	5349.245	1.000

a. Observed Power $(1-\beta)$ computed using alpha = .05
b. R Squared = .599 (Adjusted R Squared = .556) based on Corrected Model
c. R Squared = .425 (Adjusted R Squared = .363) based on Corrected Model
d. R Squared = .921 (Adjusted R Squared = .912) based on Corrected Model
e. Fitness measured relative to global max. fitness (f_m)

Table 5.58 Spearman's Rho Correlation for Hypothesis 9

			λ_u	f_t	$\overline{f_t}$	t_s	C_f	$\overline{C}$
Spearman's Rho (ρ)	λ_u (0 to 2.5)	Correlation Coefficient	1.000	.578**	.309**	-.765**	.166**	.637**
		Sig. (2-tailed)	.	.000	.000	.000	.000	.000
		N	510	510	510	510	510	510
	λ_u (0 to 50)	Correlation Coefficient	1.000	.065**	-.077**	-.079**	.056**	.110**
		Sig. (2-tailed)	.	.001	.000	.000	.005	.000
		N	2525	2525	2525	2525	2525	2525

a. Fitness measured relative to global max. fitness (f_m)
*. Correlation is significant at the 0.05 level (2-tailed).
**. Correlation is significant at the 0.01 level (2-tailed).

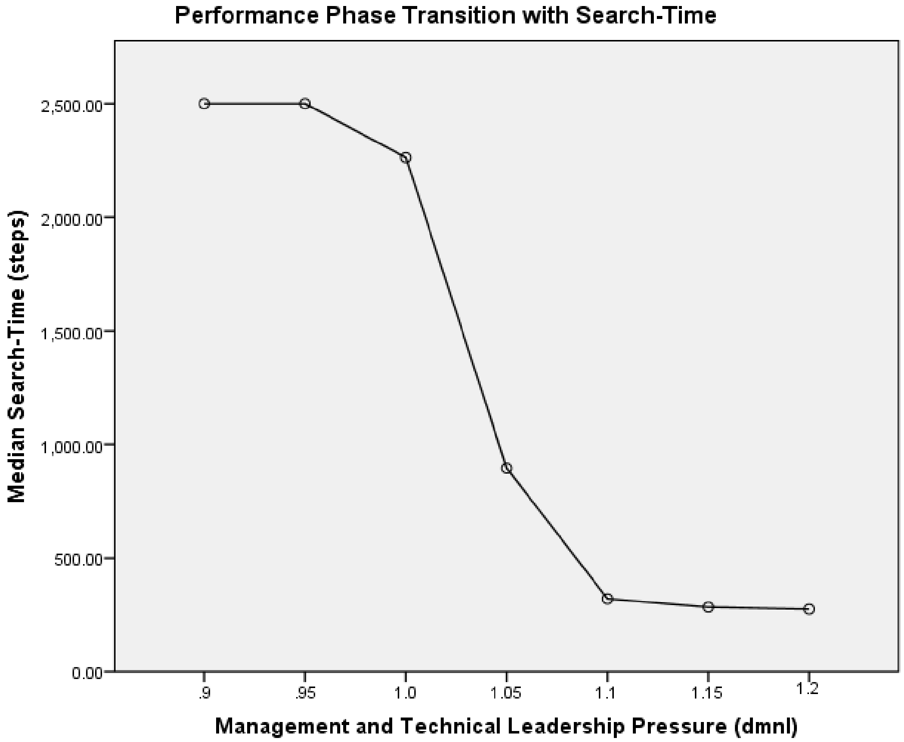


Figure 5.9 Phase Transition in Search-Times Over Given Range for λ_u

Table 5.59 Significance and Hypothesis Testing for Hypothesis 9

Null Hypothesis	Test	Stat.		Decision [a b c d]
The mean differences between the means of t_s for different values of λ_u is 0.	ANOVA F-test [a]	Wide Range	0.000 [a b] Sig.	Reject the Null Hypothesis
		Transitional Range	0.000 [a b] Sig.	
The relationship between λ_u and t_s is not negatively correlated.	Pearson's R (cf. Appendix AA)	Wide Range	-0.126 [c]	
		Transitional Range	-0.835 [c]	
The relationship between λ_u and t_s is not negatively correlated.	Spearman's Rho (ρ)	Wide Range	-0.765 [c]	
		Transitional Range	-0.079 [c]	

a. Observed power for each test using between subject effects equaled 1.00 for t_s
b. Observed Power (1-β) computed using alpha = .05
c. Correlation is significant at the 0.01 level (2-tailed)
d. Asymptotic significances are displayed. The hypothesis test uses an alpha of 0.05.

The results from this discussion have important implications for the DAU and its management, chiefly that although there does exist a statistically significant correlation between management involvement and design performance, the relative strength of any correlation diminishes past certain thresholds (e.g. search-times level off for λ_u > 1.1) and the relationships between the management and technical pressure (λ_u) parameter and performance remains multifaceted. Appendix AA demonstrates that increased levels of λ_u > 1.5 may negatively affect the average fitness of the design-team while offering little to no benefit for the remainder of the DAU.

The translation of this particular experiment into the design world corresponds to the role of goals and the involvement of a singular decision-maker (or set of unique decision-makers) in the design process. The resource holder responsible for decision-making in design must continually find the right degree of involvement in the design decisions of the DAU. Unlike the agent-based decision-making units responsible for exploring the design landscape, the management and technical leadership parameter refers to the existence of a separate decision-making entity outside of the design and exploration activities. This decision-maker serves as an arbitrator whose influence on the DAU comes through the provisioning of resources and supplies. In effect, this arbitrating influence must balance its level of involvement in the design process to on one hand ensure an adequate exploration of design alternatives while also on the other ensuring the timely alignment of the DAU with achieving fitness objectives (either at some minimum level or at some value greater). In cases where λ_u > 1.0, the DAU management system either intentionally or mistakenly sets its fitness goals above the minimally acceptable design threshold to motivate the DAU to improve its performance by providing a more difficult goal. Although the DAU may never achieve this new fitness expectation, by the arbitrating process probabilistically rewarding increasingly fit concepts the design process has an increased likelihood of attaining the best of the design alternatives discovered thusly. Interestingly, the data suggests that by reasonably setting the fitness goal higher than the "try your best" goals (λ_u = 1.0) to a more "challenging" goal of approximately λ_u = 1.5 (i.e. 50% higher than what the baseline requires) the DAU achieved more than a one standard deviation (σ = 8.755%) higher result. Specifically this meant that the DAU improved its median final fitness to global fitness values, over the course of the multiple simulations, from approximately 85% to nearly 95%. Furthermore, the results showed that the addition of the goal yielded a statistically significant higher degree of group clustering (final and average values). This overall result comports well with similar findings discussed by Schlick (2009), including from 10 empirical studies on group goals and performance by O'Leary-Kelly, Martocchio, and Frink (1994). These studies similarly found a slightly less than one standard deviation improvement to performance for groups with challenging goals versus groups that do not have challenging goals.

However, the simulation also shows that the setting of goals to unobtainable levels beyond a particular threshold can negatively affect the average fitness of the DAU as it explores the design landscape. In the real world, this corresponds to the possibility of having goals rejected by the design-team due to its lack of attainability and the demotivation of a team as it experiences repeated failures. More specifically, in the simulation, having management and technical leadership pressure (i.e. goal expectations) too high discounts new design concepts prematurely and prevents the development of these concepts to their maximum potential (i.e. to their fitness peaks) where they might otherwise succeed. Conversely, the data shows that having the DAU consider design alternatives less than the minimum fitness objective (i.e. λ_u < 1.0) required by the design results in extremely deleterious impacts to the ability of the DAU to come to agreement on solutions, especially on rugged or semi-rugged design landscapes as used in this test. Without leadership to manage the design process towards at least the established fitness objectives, less than ideal (i.e. insufficiently fit) design solutions gain self-perpetuating constituencies that prevent the design processes from coming to consensus and choosing a final design concept. Although the research explored a constant level of management involvement through analogy to the management and technical leadership parameter, managing the design process represents a dynamic challenge that theoretically. As such, the application of this parameter could benefit from the strategic application and use of inputs arising during the progression of the DAU in its exploration and exploitation activities. Knowing the importance of a baseline level of management and technical leadership pressure (λ_u), the research turns to the question of whether a strategy for managing the DAU can appropriately incentive the DAU to reach design decisions faster.

5.1.10 Hypothesis 10 – Situational Management

As seen in the previous hypothesis, the degree of constant management and technical leadership pressure (λ_u), although statistically significant, proved most important over a limited and particular range (approximately zero to 150%). As discussed, this pressure represents a degree of allowable fitness deficiency for designers by the DAU management system. In effect, increasing the parameter value increases the selectivity of design concepts and corresponds to a changing threshold of acceptable concepts for the DAU pursue. Designers with fitness above this threshold are increasingly more likely to successfully advocate for and receive new resources, which in the case of the C^2D simulation increases the ability and likelihood of a designer to grow their design constituency. As a design constituency increases its rank, the increased selectivity in turn results in a virtuous cycle for the beneficiaries (i.e. those designers with higher fitness). As a design concept benefits from this policy and takes hold, it increases in perpetuity the likelihood of new designers originating, radially out, from the conceptual locus of the benefiting design constituency until arriving at consensus. This dynamic mirrors the natural selection dynamic over time, an effect akin to the likelihood of a species adopting a beneficial mutation overtime. However, unlike natural selection, management has the ability to affect changes swiftly, artificially punctuating the inherent system equilibrium and inducing the adoption of a design concept for the DAU. The following hypothesis deals with the question of turning the policy of selectivity into a dynamic strategy. The research structures this strategy with the hope of encouraging consensus building while minimizing the time spent in protracted negotiations between competing design constituencies. The simulation implements this strategy by increasing gradually (and linearly) the selectivity of the DAU management system over time when (and only when) the average of the DAU has achieved sufficient fitness. The research considers whether this increasing degree of technical leadership leads to improved performance outcomes as predicted or whether it may actually hamper the fitness and search-times of the DAU.

Alternative Hypothesis 11: Selectively increasing management and technical leadership pressure (λ_u) leads to reduced search-times (t_s) and decreased design-team final fitness values (f_t).

$$f(\lambda_u, t) \;\tilde{\propto}\; -t_s \;\; \wedge \;\; f(\lambda_u, t) \;\tilde{\propto}\; f_t \qquad\qquad H_{a_{10}}$$

Null Hypothesis 11: Selectively increasing management and technical leadership pressure (λ_u) neither reduces search-times (t_s) nor decreases design-team final fitness values (f_t).

$$f(\lambda_u, t) \not\approx {}^{k}/_{t_s} \;\; \wedge \;\; f(\lambda_u, t) \not\approx k * f_t \qquad k = \text{constant} \qquad\qquad H_{o_{10}}$$

5.1.10.1 Design of experiments

The design of experiments examines the search-times (t_s) and the final fitness values of design-teams (f_t) with and without the application of the management strategy. The design of experiments follows a similar setup as used earlier, and follows below in Table 5.60 and Table 5.61. The management and technical leadership pressure parameter (λ_u) corresponds to an initial value; the application of the strategy increases this parameter value over time (ticks) during periods when the DAU achieves a sufficient average fitness. This experimental setup results in 582 simulations.

Table 5.60 Behavior Space Implementation in Simulation for Hypothesis 10

n	["team-size" 4]	mdt	["max-downtime" 10 30]
p	["prob_of_newcomer" 50]	Seed	["seed" random]
q	["prop_to_repeat" 85]	Strategy	["consensus_strat" true false]
λ_u	["management_pressure" [1 .07 1.5]]	Fitness Goal	["stopping_fitness" 92]
S	["Smoothness" 20]	Repetitions	30
m	["allowable_diversity" 50]	Commands	Setup, Go, Repeat

Table 5.61 Default Parameter Settings for Runs for Hypothesis 10

<table>
<tr><td></td><td>Default Modelling Dynamics
(Age?, Max-Downtime?, Hill-Climbing?, and Coalesce?)</td><td>On</td></tr>
<tr><td></td><td>Require Same Stopping Point Strategy
(Consensus)</td><td>On</td></tr>
<tr><td rowspan="3">Continuous Diversity Management Strategy</td><td>Pause and Restart Diversity Strategy</td><td rowspan="3">On</td></tr>
<tr><td>Dynamic Diversity Strategy</td></tr>
<tr><td>Stop Diversity if Average of the DAU is Fit Strategy</td></tr>
<tr><td rowspan="2">Management Strategy for Consensus Building</td><td>Stop Prolonged Decision Making Strategy</td><td>On*</td></tr>
<tr><td>Management Pressure (λ_u) Increase per Tick</td><td>0.030 dmnl</td></tr>
</table>

** Turned on and off as a group per main hypothesis objective.*

5.1.10.2 Testing Methodology

The analysis relies on an ANOVA to test for the statistical significance of relationships. In order to determine the correlations between the data, the analysis utilizes a linear regression to determine the Pearson's R correlation value. Finally, the analysis compares the data in two groupings, one with the strategy applied and one without the application of the strategy, by splitting the data file into corresponding sets based on the strategy state (i.e. on or off). The analysis also uses a Wilcoxon rank comparison of these data sets to verify any significance detected as part of the original ANOVA. In addition, the research captures the descriptive statistics for the comparison of the with- and without-strategy groups. Finally, the analysis runs a bivariate correlation to capture the strengths of any relationship to support further any statistical finding.

5.1.10.3 Results and Observations

The results for the experiment highlight the statistically significant correlation between the application of the consensus strategy and the improvement of final fitness values and lower design times. The analysis establishes the statistical significance of these relationships using an ANOVA and Wilcoxon Ranked Sign Test in Tables 5.62 and 5.65 respectively. The correlational information and descriptive statistics also follow in Tables 5.63 and 5.64 respectively. Finally, the analysis includes a summary of these findings as they relate to the hypothesis in Table 5.66.

Table 5.62 Summary of Between Subject Effects ANOVA for Hypothesis 10

Source	Dependent Variable[b]	Type III Sum of Squares	Df	Mean Square	F (1,479)	Sig.	Noncent. Parameter	Obs. Power[a]
Consensus Management Strategy	f_t	.031[c]	1	.031	21.401	.000	21.401	.996
	$max(f_t)$	1.065E-005[d]	1	1.065E-005	.020	.889	.020	.052
	$\overline{f_t}$	.164[e]	1	.164	89.432	.000	89.432	1.000
	C	.049[f]	1	.049	20.428	.000	20.428	.995
	$\overline{C}$	.008[g]	1	.008	82.944	.000	82.944	1.000
	t_s	11821474.133[h]	1	11821474.133	164.064	.000	164.064	1.000

a. Observed Power $(1-\beta)$ computed using alpha = .05
b. Fitness variables measured relative to global maximum fitness values (f_m)
c. R Squared = .069 (Adjusted R Squared = .038)
d. R Squared = .026 (Adjusted R Squared = -.007)
e. R Squared = .310 (Adjusted R Squared = .287)
f. R Squared = .334 (Adjusted R Squared = .312)
g. R Squared = .058 (Adjusted R Squared = .027)
h. R Squared = .268 (Adjusted R Squared = .243)

Table 5.63 Comparison of Correlations for Hypothesis 10

Consensus Management Strategy		t_s	f_t	$max(f_t)$	$\overline{f_t}$	C_f	$\overline{C}$	λ_u	mdt
Spearman's Rho (ρ)	Correlation Coefficient	-.487**	.186**	-.008	-.376**	.233**	.408**	-.042	.062
	Sig. (2-tailed)	.000	.000	.867	.000	.000	.000	.352	.171
	N	496	496	496	496	496	496	496	496
Pearson R Correlation	Correlation Coefficient	-.481**	.202**	-.015	-.365**	.208**	.373**	-.041	.084
	Sig. (2-tailed)	.000	.000	.744	.000	.000	.000	.357	.062
	N	496	496	496	496	496	496	496	496

**. Correlation is significant at the 0.01 level (2-tailed)

Table 5.64 Comparison of Descriptive Statistics with Strategy Application Hypothesis 10

Grand Mean						
Diversity Management Strategy	Dependent Variable	N	Mean	Std. Error	95% Confidence Interval	
					Lower Bound	Upper Bound
Strategy On	f_t	240	.9758	.02826	.87	1.00
	$max(f_t)$	240	.9830	.02263	.92	1.00
	$\overline{f_t}$	240	.8702	.04712	.74	.97
	t_s	240	300.7000	229.32474	44.00	1000.00
	C_f	240	.8446	.06056	.66	1.00
	$\overline{C}$	240	.8338	.01132	.79	.87
Strategy Off	f_t	240	.9597	.04656	.71	1.00
	$max(f_t)$	240	.9833	.02390	.91	1.00
	$\overline{f_t}$	240	.9071	.04767	.78	.99
	t_s	240	614.5667	332.11994	53.00	1000.00
	C_f	240	.8243	.03218	.75	.92
	$\overline{C}$	240	.8256	.00973	.79	.86

Table 5.65 Test of Significance Using Wilcoxon Signed Rank Test for Hypothesis 10

Test Statistics [a]

Strategy Off Value - Strategy On Value	f_t	$max(f_t)$	$\overline{f_t}$	t_s	C_f	$\overline{C}$
Z	-4.119[b]	-.415[c]	-8.149[c]	-9.590[c]	-4.410[b]	-7.937[b]
Asymp. Sig. (2-tailed)	.000	.678	.000	.000	.000	.000

a. Wilcoxon Signed Ranks Test

b. Based on positive ranks.

c. Based on negative ranks.

Table 5.66 Significance and Hypothesis Testing for Hypothesis 10

Null Hypothesis	Test	Stat.	Decision [a b c d e f]
The mean (median) differences between the means (values) of t_s with a consensus management strategy applied and without one applied is 0.	ANOVA F-test [a]	0.000 [a b] Sig.	Reject the Null Hypothesis
	Wilcoxon Signed Rank Test	0.000 [c] Sig.	
The mean (median) differences between the means (values) of f_t with a consensus management strategy applied and without one applied is 0.	ANOVA F-test [a]	0.000 [a b] Sig.	
	Wilcoxon Signed Rank Test	0.000 [d] Sig.	
The relationship between t_s and the consensus management strategy is not negatively correlated.	Pearson's R	-.481 [e]	
	Spearman's Rho (ρ)	-.487 [e]	
The relationship between f_t and the consensus management strategy is not positively correlated.	Pearson's R	.202 [e]	
	Spearman's Rho (ρ)	.186 [e]	

a. Observed power for each test using between subject effects equaled 1.00
b. Observed Power (1-β) computed using alpha = .05
c. Based on Negative Ranks
d. Based on Positive Ranks
e. Correlation is significant at the 0.01 level (2-tailed)
f. Asymptotic significances are displayed. The hypothesis test uses an alpha of 0.05.

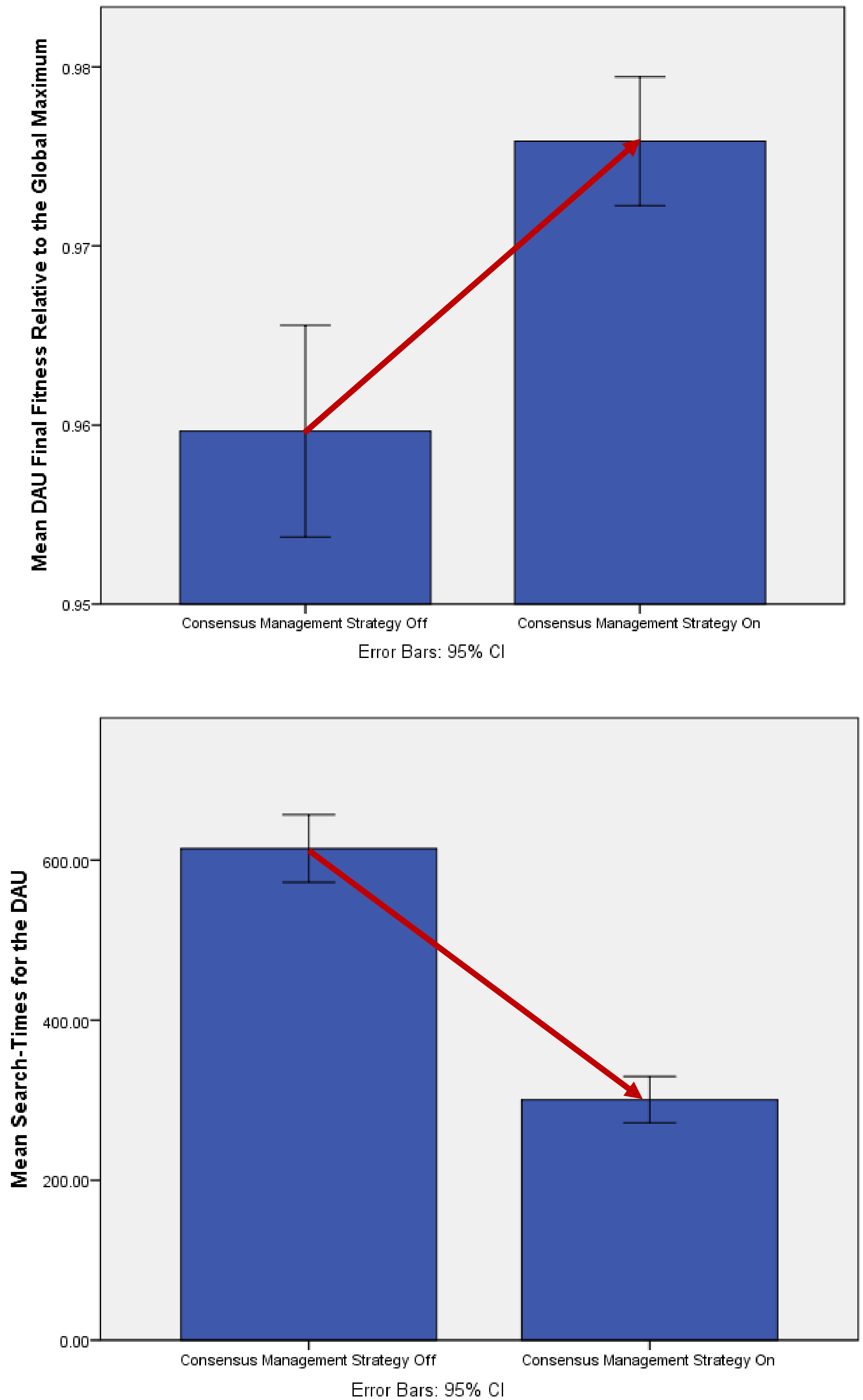


Figure 5.10 Mean Plots with Strategy for Hypothesis 10

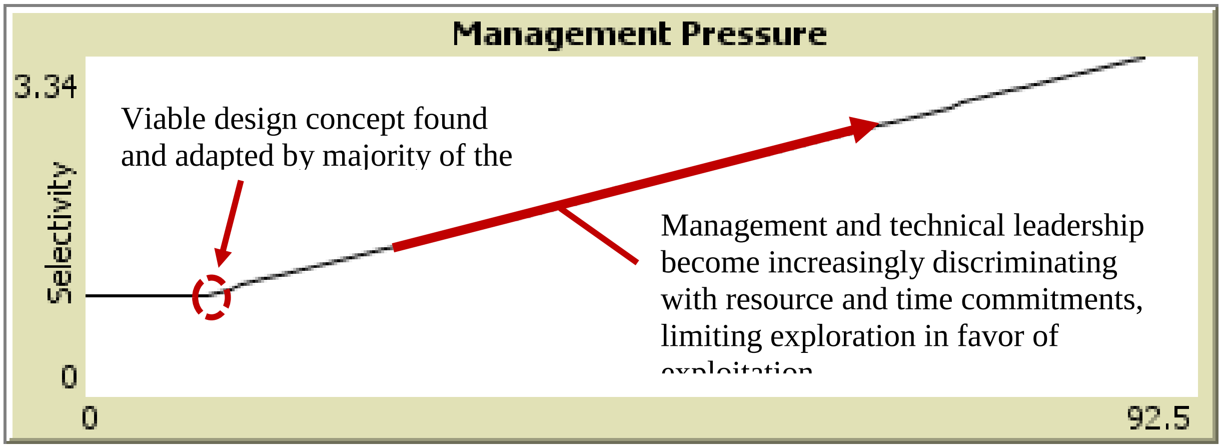


Figure 5.11 Plot of the Consensus Management Strategy during an Average Simulation

The results of the analysis reveal several insights relevant to the policy of the DAU and its management system. First, when compared to the previous hypothesis, it reveals that the use of a dynamic strategy improves both the search-times (t_s ≅ 301 ticks versus 328 ticks) and overall design-fitness values (f_t ≅ 97.6% fitness versus 94.8% fitness). The strategy operates by allowing a period of exploration long enough to allow for the average fitness of the designers to meet or exceed the minimally acceptable fitness objective, as seen in Figure 5.11. After this point and whilst fitness remains sufficiently at or above the fitness threshold, the management and technical leadership pressure gradually increases by the same amount with each tick. In essence, once the DAU identifies a likely solution (or set of solutions) the DAU works to build consensus around a design and the management system works to optimize this process by funneling resources from, probabilistically speaking, underperforming concepts to higher performing concepts. This finding alludes to the need for a management system to be adaptable to the stage of the design process, using data from the design process to gradually move from a mode of exploration to mode of exploitation.

The power of the C^2D simulations remains in their adaptability. For instance, although a previous diversity management strategy ramped diversity gradually higher with time (as discussed appeared in Hypothesis 7), the simulations can easily modify various configurations of strategies that correspond to different desired design behaviors. In particular, the research modifies this previously discussed strategy by limiting its implementation to an incremental or evolutionary design focus (as opposed to a strategy that allows for a more complete exploration of the design landscape), *i.e.* diversity remains either at a constant level or at zero.

5.1.10 *Hypothesis 11 – Incremental Design Evolution*

A common approach for many engineering design-firms centers on incremental improvements and incremental evolutionary design, as opposed to revolutionary or radical concept development. These approaches center their exploration on possible design solutions within their local neighborhoods on the design landscape, which offers benefits in terms of more easily aligning their processes with internal expertise and experience. Although this sometimes benefits a DAU by foregoing the need to recruit and accommodate large numbers of new disciplines and subject-matter experts within the firm, it also potentially limits its efficacy. In essence, this approach centers on managing diversity at a set level of acceptable exploration at any instance in time. In the simulation, this corresponds to a limitation on how many patches away from another agent can any newcomer join the DAU. As opposed to Hypothesis 7 where diversity continually rose with each tick when the DAU average remained less than the fitness objective, here the diversity remains the same. The strategy tested here operates by eliminating allowable diversity once the average fitness of the DAU reaches its fitness objective. This differs from the test of a constant level of diversity by allowing the DAU to turn it on or off selectively (i.e. its willingness to explore new concepts). In the event that the fitness average again falls beneath the fitness average of the DAU, this strategy reverts the allowable diversity of newcomers (m) back to its initial values (m_i). The hypothesis associated with this research question follows:

Alternative Hypothesis 10: Selectively eliminating the diversity of newcomers (m) reduces search-times (t_s) and decreases design-team final fitness values (f_t).

$$f_t|_{m(t)} > f_t|_m \quad \wedge \quad t_s|_{m(t)} < t_s|_m$$

$$\forall\, t \mid \overline{f_t} > f_{objective}\colon\ m = 0 \ \ \wedge \ \ \forall\, t \mid \overline{f_t} \leq f_{objective}\colon\ m = m_i \qquad H_{a_{10}}$$

Null Hypothesis 10: Selectively eliminating the diversity of newcomers (m) reduces search-times (t_s) and decreases design-team final fitness values (f_t).

$$f_t|_{m(t)} \ngtr f_t|_m \quad \wedge \quad t_s|_{m(t)} \nless t_s|_m$$

$$\forall\, t \mid \overline{f_t} > f_{objective}\colon\ m = 0 \ \ \wedge \ \ \forall\, t \mid \overline{f_t} \leq f_{objective}\colon\ m = m_i \qquad H_{o_{10}}$$

5.1.11.1 Design of experiments

The design of experiments examines the search-times (t_s) and the final fitness values of design-teams (f_t) with and without the application of the incremental design evolution strategy discussed. The design of experiments follows a similar setup as used earlier, and follows below in Table 5.67 and Table 5.68. The maximum allowable diversity (m) corresponds to a fixed value over the runs. The strategy eliminates any allowable diversity once the DAU achieves a sufficient average fitness (i.e. it focuses on exploitation). This experimental setup results in 400 simulations.

Table 5.67 Behavior Space Implementation in Simulation for Hypothesis 11

n	["team-size" 4]	mdt	["max-downtime" 40]
p	["prob_of_newcomer" 50]	Seed	["seed" random]
q	["prop_to_repeat" 85]	Strategy	["incremental_evolution" true false]
λ_u	["management_pressure" 1]	Fitness Goal	["stopping_fitness" 92]
S	["Smoothness" 20]	Repetitions	30
m	["allowable_diversity" 30 50]	Commands	Setup, Go, Repeat

Table 5.68 Default Parameter Settings for Runs for Hypothesis 11

	Default Modelling Dynamics (Age?, Max-Downtime?, Hill-Climbing?, and Coalesce?)	On
	Require Same Stopping Point Strategy (Consensus)	On
	Pause and Restart Diversity Strategy	Off
	Dynamic Diversity Strategy	Off
Management Strategy for Incremental Design Evolution	Stop Diversity if Average of the DAU is Fit Strategy	On*
Management Strategy for Consensus Building	Stop Prolonged Decision Making Strategy	On
	Management Pressure (λ_u) Increase per Tick	0.030 dmnl

** Turned on and off as a group per main hypothesis objective.*

5.1.11.2 Testing Methodology

The analysis compares the data in two groupings: the first grouping includes the resulting data from the simulation with the evolutionary design strategy applied and the other group includes the resulting data from the simulation without the application of the evolutionary design strategy. To do this, the analysis splits the resulting simulation data file into two separate data sets based on state of the strategy (i.e. on or off). The analysis then applies a Wilcoxon Signed Ranks Test to determine the significance, if any, between these two groups across multiple simulations. Further, the analysis similarly includes an ANOVA to test for the statistical significance of the strategies, an overall comparison of the descriptive statistics of the two groups, and a bivariate correlation to capture the strengths of any relationship to support further any statistical finding. Finally, the test, although outside the scope of the initial hypothesis, examines whether or not a statistically significant difference exists in this Incremental Evolutionary Design Strategy and the approach from the Continual Diversity Management Strategy highlighted earlier in Hypothesis 7.

5.1.11.3 Results and Observations

For the given simulations, the Incremental Design Evolution Strategy does not demonstrate any statistically significant effect. The Wilcoxon Signed Ranks Tests demonstrates this finding in Table 5.69. This is similar to the findings from the ANOVA described in Appendix AC. Additionally, the appendix includes descriptive statistics and a comparison of any correlations, although the applied tests detected no statistically significant findings. As a result, the analysis retains the null-hypothesis as outlined in Table 5.70 below.

Table 5.69 Wilcoxon Signed Ranks Test for Hypothesis 11

Test Statistics [a]

Values for Strategy Off – Strategy On	t_s	$\overline{f_t}$	f_t	$\max(f)$	C_f	$\overline{C_t}$
Z	-.536[b]	-.632[b]	-.798[c]	-.109[b]	-.816[c]	-.005[c]
Asymp. Sig. (2-tailed)	.592	.527	.425	.913	.414	.996

a. Wilcoxon Signed Ranks Test

b. Based on positive ranks.

c. Based on negative ranks.

Table 5.70 Significance and Hypothesis Testing for Hypothesis 11

Null Hypothesis	Test	Sig.	Decision
The mean (median) differences between the means (values) of t_s **with** versus **without** the application of the Incremental Design Evolution Strategy is 0.	ANOVA F-test	0.779	Retain the Null Hypothesis
	Wilcoxon Signed Rank Test	0.592	
The mean (median) differences between the means (values) of f_t **with** versus **without** the application of the Incremental Design Evolution Strategy is 0.	ANOVA F-test	0.519	
	Wilcoxon Signed Rank Test	0.425	

Asymptotic significances are displayed. The hypothesis test uses an alpha of 0.05.

Although the Incremental Design Evolution is not significant, the analysis revisits and compares this strategy with the earlier Continuous Diversity Management strategy in Figure 5.12 and Table 5.71. As seen in Figure 5.12, the difference in strategy is the ability to increase the diversity of the design-team (and in effect the number of accessible feasible design solutions) with time. The results show that the two strategies do result in statistically significant differences.

Table 5.71 Wilcoxon Signed Ranks Test for Hypothesis 11

Test Statistics [a]

Difference in Values for the Different Strategies	t_s	$\overline{f_t}$	f_t	$\max(f)$
Z	-12.057[b]	-12.174[b]	-10.836[b]	-11.777[b]
Asymp. Sig. (2-tailed)	.000	.000	.000	.000

a. Wilcoxon Signed Ranks Test

b. Based on negative ranks.

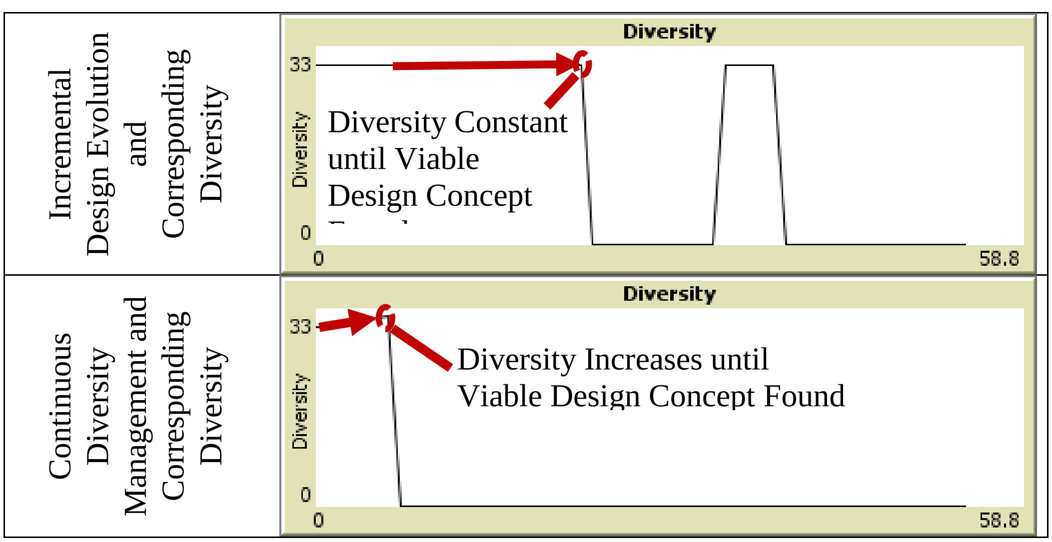


Figure 5.12 Comparison of DAU Diversity Profiles between Different Strategies

From the perspective of the management system, these findings suggest that, for a DAU with a static diversity level, a quick transition between exploration and exploitation offers no benefit to the DAU. Consider the case of a mature product development organization that limits their design activities to incremental product improvements in their product space, focusing on minor adjustments to existing product lines. These organizations, as a result, often maintain static levels of diversity. For instance, a given product line in these firms would already have a well-understood set of characteristics for their needed designers (e.g. an application-specific integrated circuit engineer). In these cases, although new design concepts may exist that would improve the value characteristics of the product or artefact in question, realization of these designs would require the organization to accept radically new design concepts (with respect to their acceptance). Such a change could include new form factors for a device, which would require new skill sets (e.g. a mechanical vibrations engineer) and possibly new equipment. In these instances, having the ability to refocus the organization quickly towards exploitation-only activities has little value according to the data as the limited degree of exploration already restricts the DAU from locating multiple feasible designs solutions.

In other words, the region of accessible design solutions from exploration remains relatively stable and finite for groups of limited and set diversity levels, such as the ones tested in this hypothesis. In the example of the product development firm, the addition of an ASIC designer, a skill-set well used by the DAU, will quickly result in the same adaptive walk to the design solution of the existing collaboration. Quantitatively, the data also supports this explanation. For instance, on average, the DAU following a Continuous Diversity Management Strategy results in design-teams that explore multiple design concepts further from one another, on average, (16.4% of the design landscape apart) versus of a smaller number of design concepts closer together, on average, for the Incremental Design Evolution Management Strategy (5.84% of the design landscape apart). Again, there is an interaction between the degree of complexity and the strategy as the number of local optima increases inversely with the smoothness of the design landscape. The following hypothesis and research question deals with examining the role of complexity in the timeliness of the DAU to locate sufficiently fit solutions.

5.1.12 HYPOTHESIS 12 – COMPLEXITY AND SEARCH-TIMES

Underlying the larger research investigation rests the role of complexity in engineering design and its relationship to the performance of the DAU. Specifically of interest in the following research question is the relationship between search-times for the DAU and the complexity of the design landscape.

Theoretically, as the complexity for the landscape increases, so too do the number of local optima. In traditional optimization explorations using the NK landscapes, the increase of local optima leads to a shortened search period or adaptive walk for agents due to a difference in modelling objectives. In the C^2D model, a set fitness minimum objectives means that an increased density of local optima on the fitness landscape does not necessarily translate into minimized search-times; in fact, much as in realistic systems, the DAU must first explore these local optima to assess their fitness. Often this exploration leads to several contingencies of designers spending resources on ideas that do not lead to successful designs, *i.e.* they become trapped on local optima of insufficient fitness. Even after applying the discussed design strategies, which help to ensure that the DAU management system favors and more rapidly promotes fit design solutions, design constituencies tend to form and increasingly become varied with increased complexity. The increased set of feasible design solutions can lead to extended periods of design negotiations and consensus. This expected behavior formed the basis of the research premise and the research question associated with the following research hypothesis:

Alternative Hypothesis 12: There exists an inversely proportional relationship between search-times (t_s) and the smoothness of the design landscape (S^*).

$$S^* \propto \frac{1}{t_s} \qquad H_{a_{12}}$$

Null Hypothesis 12: There does not exist an inversely proportional relationship between search-times (t_s) and the smoothness of the design landscape (S^*).

$$\lambda S^* \not\approx \frac{1}{t_s}, \qquad \lambda = \text{constant scalar} \qquad H_{o_{12}}$$

5.1.12.1 Design of experiments

The design of experiments examines the search-times (t_s) and, although outside of the hypothesis, the final fitness values of the design-teams (f_t) for various degrees of landscape smoothness (S). This parameter represents the inverse of design complexity as outlined in Chapter 3. The design of experiments follows a similar setup as used in previous tests and follows below in Table 5.72 and Table 5.73. This setup also tests for various degrees of smoothness (S) using the management strategies discussed.[44] This experimental setup results in 1200 simulations.

Table 5.72 Behavior Space Implementation in Simulation for Hypothesis 12

n	["team-size” 4]	mdt	["max-downtime” 40]
p	["prob_of_newcomer” 50]	Seed	["seed" random]
q	["prop_to_repeat" 85]	Strategy	[“consensus_strat” true false]
λ_u	["management_pressure" 1]	Fitness Goal	[“stopping_fitness” 92]
S	[“Smoothness” [0 20 100]]	Repetitions	30
m	[“allowable_diversity” 50]	Commands	Setup, Go, Repeat

Table 5.73 Default Parameter Settings for Runs for Hypothesis 12

<table>
<tr><td></td><td>Default Modelling Dynamics
(Age?, Max-Downtime?, Hill-Climbing?, and Coalesce?)</td><td>On</td></tr>
<tr><td></td><td>Require Same Stopping Point Strategy
(Consensus)</td><td>On</td></tr>
<tr><td rowspan="3">Continuous Diversity Management Strategy</td><td>Pause and Restart Diversity Strategy</td><td rowspan="3">On</td></tr>
<tr><td>Dynamic Diversity Strategy</td></tr>
<tr><td>Stop Diversity if Average of the DAU is Fit Strategy</td></tr>
<tr><td rowspan="2">Management Strategy for Consensus Building</td><td>Stop Prolonged Decision Making Strategy</td><td>On</td></tr>
<tr><td>Management Pressure (λ_u) Increase per Tick</td><td>0.030 dmnl</td></tr>
</table>

[44] Previous statistical testing (cf. Appendices R and X) has included S and has already provided statistical insights for cases with no management strategy employed. The results are consistent with the findings following from this design of experiments.

5.1.12.2 Testing Methodology

The analysis relies on an ANOVA to test for between subject effects. In order to determine the correlations between the data, the analysis utilizes a linear regression to determine the Pearson's R correlation value. For comparison purposes, the analysis also calculates the nonparametric Spearman's rank correlation coefficient to capture any correlations resulting from possible nonlinear relationships.

5.1.12.3 Results and Observations

The summary of between subject effects captured from the ANOVA follows in Table 5.74, with the complete table captured in Appendix AD. The ANOVA confirms a statistically significant relationship between the landscape smoothness (S) and the resulting final fitness values (f_t), the average fitness values $\overline{(f_t}$), and the total search-times (t_s) for the DAU when consensus is required. As discussed previously, the consensus requirement imposes the need to have one final design solution before terminating the simulation. When consensus is not required, the analysis demonstrates a statistically significant relationship between the landscape smoothness (S) and both the average fitness values $\overline{(f_t}$) and the search-times (t_s) for the DAU. The analysis includes a bivariate calculation, using both Pearson R correlation and Spearman's Rho correlation, between factors to calculate the strength of these relationships as seen in Table 5.75. These correlations show a moderately strong correlation between the landscape smoothness (S) and the search-times (t_s) for the DAU. The overall statistical findings follow as part of Table 5.76 and Figure 5.13.

The analysis uses the smoothness of the landscape (S) as an intermediary variable for measuring the influence of complexity, as discussed in Chapter 3. Using this approach, the results from the analysis show that as the complexity of the design space increases the design times also rise, this statistically significant relationship holds true regardless of the need for any negotiation or consensus process as expected. In other words, the more complex a design landscape the longer it takes the DAU to identify and adapt to sufficiently fit design solutions. However, what also emerges from the data is the statistically significant negative relationship of moderate strength between the complexity of design tasks and the final fitness values achieved by a design team when requiring a final design solution.

Table 5.74 ANOVA between Subject Effects for Hypothesis 12

Source	Dep. Var.	Type III Sum of Squares	df	Mean Square	F (5, 594)	Sig.	Noncent. Param.	Obs. Power[k]
Smoothness (Conesus Not Required)	t_s	1371513.328	5	274302.666	37.824	.000	189.120	1.000
	f_t	.001	5	.000	.529	.754	2.646	.197
	$\overline{f_t}$	.245	5	.049	21.991	.000	109.953	1.000
Smoothness (Consensus is Required)	t_s	7237669.153	5	1447533.83	37.966	.000	189.830	1.000
	f_t	.145	5	.029	23.158	.000	115.791	1.000
	$\overline{f_t}$	.267	5	.053	27.088	.000	135.439	1.000

Table 5.75 Comparison of Correlations with Smoothness for Hypothesis 12

	Consensus Not Required		t_s	f_t	$max(f_t)$	$\overline{f_t}$	C_f	$\overline{C}$
Correlations with Landscape Smoothness	Spearman's Rho (ρ)	Correlation Coefficient	-.571**	-.067	-.067	-.311**	-.185**	.132**
		Sig. (2-tailed)	.000	.103	.100	.000	.000	.001
		N	600	600	600	600	600	600
	Pearson R Correlation	Correlation Coefficient	-.419**	-.018	-.025	-.340**	-.168**	.181**
		Sig. (2-tailed)	.000	.652	.542	.000	.000	.000
		N	600	600	600	600	600	600
	Consensus Required		t_s	f_t	$max(f_t)$	$\overline{f_t}$	C_f	$\overline{C}$
Correlations with Landscape Smoothness	Spearman's Rho (ρ)	Correlation Coefficient	-.615**	.438**	.473**	.371**	.029	-.290**
		Sig. (2-tailed)	.000	.000	.000	.000	.483	.000
		N	600	600	600	600	600	600
	Pearson R Correlation	Correlation Coefficient	-.464**	.377**	.463**	.356**	.031	-.291**
		Sig. (2-tailed)	.000	.000	.000	.000	.445	.000
		N	600	600	600	600	600	600

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

Table 5.76 Significance and Hypothesis Testing for Hypothesis 12

Null Hypothesis	Test	Sig. [a]	Decision [a b c d]
The mean differences between the means of t_s with different levels of S is 0.	ANOVA F-test (With Consensus)	0.000 [b]	Reject the Null Hypothesis
	ANOVA F-test (Without Consensus)	0.000 [c]	

a. Observed Power $(1-\beta)$ is 1.0 for both cases and was computed using alpha = .05
b. R Squared = .242 (Adjusted R Squared = .236)
c. R Squared = .241 (Adjusted R Squared = .235)
d. Asymptotic significances are displayed. The hypothesis test uses an alpha of 0.05.

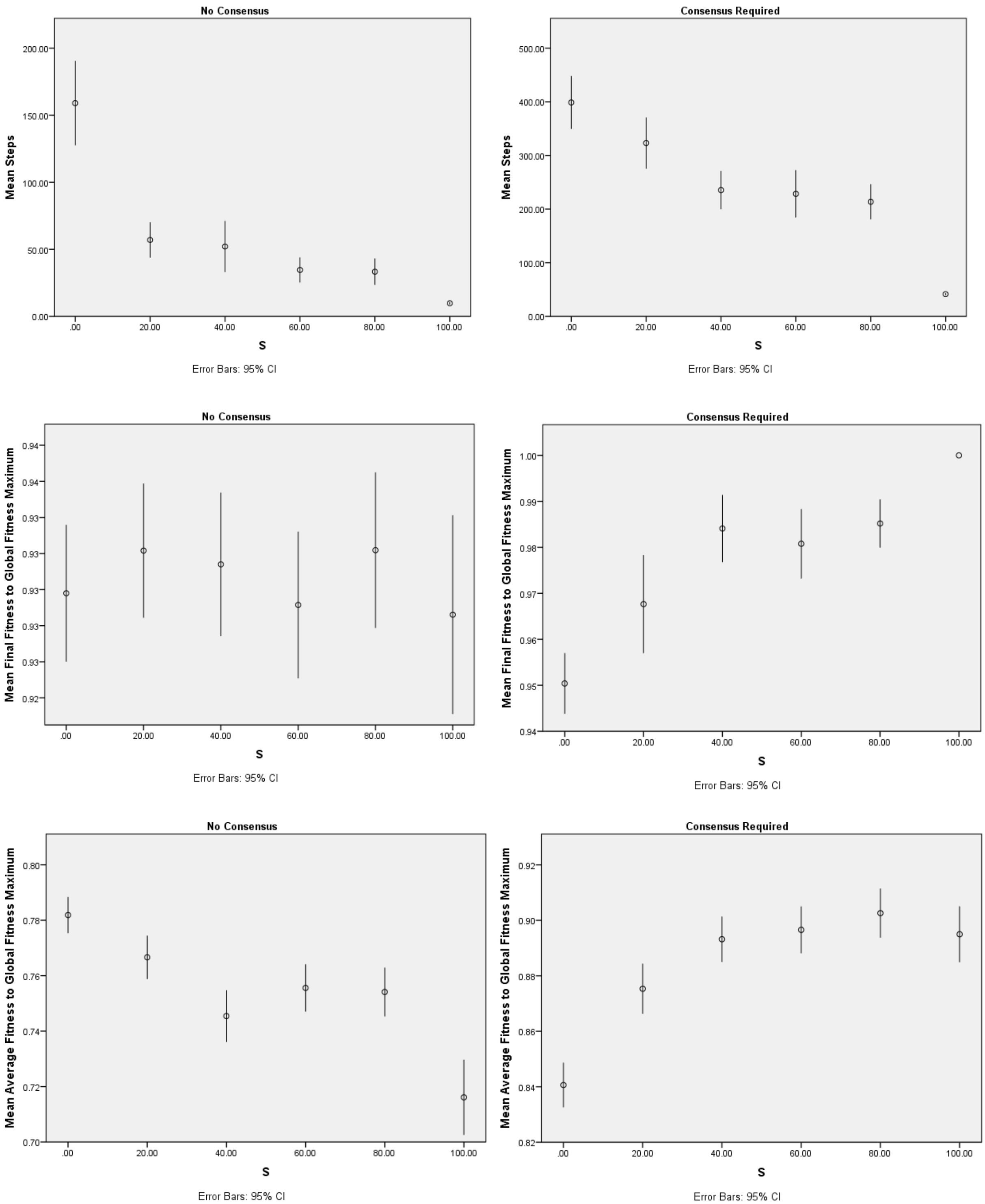


Figure 5.13 Plot of Key DAU Performance Characteristics with Smoothness

For increased levels of design complexity, the DAU has to consider several more design possibilities and overcome an increasing degree of unfit local optima (e.g. the quantity of local optima logarithmically increases from one to the expected value $E(opt) = (2^{N-1}/(N+1))$ for cases of maximally rugged landscapes as the size of the landscape increases). In other words, as the size of landscape and the complexity (measured by K) increases, the mean of the local optima tend to move closer to the expected mean of a uniform random distribution (i.e. one-half in the simulation).[45] Because of the fixed size of the design-landscape used in these simulations runs (i.e. $N = 13$) the corresponding maximum $K = N - 1 = 12$ results in the mean of local optima (as complexity reaches its maximum) approaching a value approximately equal to 0.66. The increased number of design possibilities coupled with their lessened fitness values results in the design-team spending more time sifting through, locating, and, finally if successful, adapting to sufficiently fit design solutions. After finding a sufficiently fit design concept, the design-team works to conclude its search and focus on the exploitation. The increase in the proportion of unfit local optima in turn means that the exploitation activities become increasingly focused on a relatively few design approaches and the overall final fitness for the DAU tends to decrease as seen in the analysis. Similarly, the time spent in driving the DAU to a single design approach logarithmically increases for increased design complexity. This increase in required search-times arises from the competing design constituencies. Although many of the corresponding design concepts represent insufficiently local optima, *i.e.* design solutions that will not work, it takes the DAU a longer period of time to analyze the relative solutions and to then negotiate a sufficient solution. Conversely, in the case of no complexity, all DAU searches of the design-landscape (i.e. adaptive walks) lead to one optimum point on the design landscape.

From the perspective of the DAU management system, the uncovered relationships between complexity and design performance have clear implications in the structuring of management strategies. The results show that structural complexity itself can without careful management lead to exaggerated search-times and lowered design outcomes as measured by final fitness. In fact, the nature of complexity shows that design solutions on average tend towards mediocracy with increased complexity, *i.e.* a loss of focus (such as unique design adaptations) tends occur given an increasingly rugged design landscape. Although the use of design strategies can certainly help to

[45] Interestingly, this parallels the concepts of biological frustration discussed in Chapter 2. The average of the overall fitness landscape gradually tends to an average degree of fitness with increased complexity.

ameliorate the performance disruptions to the DAU, the analysis also shows that even with effective design management strategies that this relationship to the ruggedness of the design landscape has a significant and moderate to strong negative relation to the performance characteristics of the DAU. As a result, the next research question investigates the ability to rearrange the design approach to minimize complexity a priori. Theoretically, by following the axiomatic rules of design discussed in Chapter 2, the DAU represents a strong opportunity to possibly further improve the design performance characteristics.

5.1.13 Hypothesis 13 – Structuring the Approach

The research previously discussed the relationship between complexity and the design landscape as part of Chapter 3. The analysis now pursues this question of structural complexity in design and specifically the size of engineering design and its complexity using equation (3.10), which provides a framework for relating the number of requirements (N) and the structuring of a design matrix to its overall complexity and interconnectedness (K). The corresponding research hypothesis follows:

Alternative Hypothesis 13: Structuring the *design matrix* $[A]$ according to the *axiomatic rules of design* $[A]^*$ reduces the required search-time for the design-team (t_s).[46]

$$t_s|_{[A]^*} < t_s|_{[A]} \qquad H_{a_{13}}$$

Null Hypothesis 13: Structuring the *design matrix* $[A]$ according to the *axiomatic rules of design* $[A]^*$ does not reduce the required search-time for the design-team (t_s).

$$t_s|_{[A]^*} \nless t_s|_{[A]} \qquad H_{o_{13}}$$

5.1.13.1 Design of experiments

The design of experiments examines the search-times (t_s) and, although outside the bounds of the hypothesis, the final fitness values of design-teams (f_t) for various design matrices, to compare the role of structural complexity. Specifically, the experiment includes a comparison of the design

[46] The axiomatic approach towards design requires minimizing information content of a design and ensuring its functional independence, as discussed in Chapter 2. In our approach, these characteristics give rise to the complexity of the design landscape.

matrices shown in Figure 5.14. In this comparison, we compare a partially coupled design to an ideal design and a fully coupled design to an ideal design. The ability to structure a design appropriately corresponds to the ability to conceive of an approach for a design that maintains the independence of functional requirements. The design of experiments follows a similar setup as used earlier, and follows below in Table 5.77 and Table 5.61. This experimental setup incorporates the preceding management strategies and results in 1800 simulations.

$[A] \rightarrow N = 3 \quad K = 1$

$$\begin{bmatrix} X & X & \\ & X & X \\ & X & X \end{bmatrix}$$

$[A]^* \rightarrow \; N = 5 \quad K = 0$

$$\begin{bmatrix} X & & & & \\ & X & & & \\ & & X & & \\ & & & X & \\ & & & & X \end{bmatrix}$$

$[A] \rightarrow N = 3 \quad K = 2$

$$\begin{bmatrix} X & X & X \\ X & X & X \\ X & X & X \end{bmatrix}$$

$[A]^* \rightarrow \; N = 9 \quad K = 0$

$$\begin{bmatrix} X & & & & & & & & \\ & X & & & & & & & \\ & & X & & & & & & \\ & & & X & & & & & \\ & & & & X & & & & \\ & & & & & X & & & \\ & & & & & & X & & \\ & & & & & & & X & \\ & & & & & & & & X \end{bmatrix}$$

The Design Matrix $[A]$ relates the Functional Requirements {FRs} to the Design Parameters {DPs}, the relationship between a FR and DP is denoted by an x in the design matrix (cf. Chapter 3).

Figure 5.14 Design Matrices under Direct Comparison in the Simulation

Table 5.77 Behavior Space Implementation in Simulation for Hypothesis 13

n	["team-size” 4]	mdt	["max-downtime” 40]
p	["prob_of_newcomer” 50]	Seed	["seed" random]
q	["prop_to_repeat" 85]	Strategy	[“consensus_strat” true false]
m	[“allowable_diversity” 50]	Fitness Goal	[“stopping_fitness” 92]
N	[“N” 9 5 3]	Repetitions	100
K	[“K” 2 1 0]	Commands	Setup, Go, Repeat

Table 5.78 Default Parameter Settings for Runs for Hypothesis 13

<table>
<tr><td></td><td>Default Modelling Dynamics
(Age?, Max-Downtime?, Hill-Climbing?, and Coalesce?)</td><td>On</td></tr>
<tr><td></td><td>Require Same Stopping Point Strategy (Consensus)</td><td>On</td></tr>
<tr><td rowspan="3">Continuous Diversity Management Strategy</td><td>Pause and Restart Diversity Strategy</td><td rowspan="3">On</td></tr>
<tr><td>Dynamic Diversity Strategy</td></tr>
<tr><td>Stop Diversity if Average of the DAU is Fit Strategy</td></tr>
<tr><td rowspan="2">Management Strategy for Consensus Building</td><td>Stop Prolonged Decision Making Strategy</td><td>On</td></tr>
<tr><td>Management Pressure (λ_u) Increase per Tick</td><td>0.030 dmnl</td></tr>
</table>

5.1.13.2 Testing Methodology

The analysis splits the resulting simulation output data into individual groups corresponding to the individual design matrices under comparison. Additionally, the analysis also then subdivides the data into separate groups corresponding to simulations that require and those that do not require consensus. The role of consensus again corresponds to the need for the DAU to reach final agreement on a single design concept, versus the ability of the DAU to locate several design concepts that on average have adequate fitness. This distinction allows the analysis to consider separately the ability of the DAU to negotiate and navigate design alternatives and its ability to identify sufficiently fit design alternatives. The analysis uses a Wilcoxon Signed Ranks Test comparison of the data sets to verify any significance detected. In addition, the research captures the descriptive statistics for the data as well as an overall ANOVA for between subject effects.

5.1.13.3 Results and Observations

The Wilcoxon Signed Ranks Tests reveals a statistically significant difference between the coupled design matrices and its theoretical corresponding ideal design matrix. The summary results from the test follow in Table 5.79. The test results suggest that a reduction in the structural complexity of a design can both lower the search times for the design-teams as well as increase the final design fitness. The descriptive statistics and overall results also show that these relationships strengthen with increased complexity (i.e. as K increases relative to N) and with the need for consensus, as seen in Appendix AE.

These findings support the Axiomatic Design approach from Suh (1999) as a valid performance-enabling framework for design. However, although important, the structuring of the design problem (specifically with respect to its structural complexity) represents a small portion of the overall factors in design when considering the DAU as a complex system. By combining strategies as well as the structuring of the design approach it is possible to help overcome design complexities. By allowing the management system to strategically position itself with respect to the technological landscape, the DAU can help improve its overall design fitness and well as time-to-market proposition. In the final section of this chapter, the research provides a sample case study to reinforce these notions. The following section provides a recap of the preceding results.

Table 5.79 Wilcoxon Signed Ranks Test for Comparing Design Matrices in Hypothesis 13

Test Statistics [a]

		N=3, K=1 Versus N=5, K=0			N=3, K=2 Versus N=9, K=0		
		f_t	$\overline{f_t}$	t_s	f_t	$\overline{f_t}$	t_s
No Consensus	Z	-1.435[b]	-8.682[c]	-1.453[b]	-6.049[c]	-7.929[c]	-1.133[c]
	Asymp. Sig. (2-tailed)	.151	.000	.146	.000	.000	.257
Consensus	Z	-5.376[c]	-3.621[c]	-4.418[b]	-3.091[b]	-8.682[c]	-4.726[b]
	Asymp. Sig. (2-tailed)	.000	.000	.000	.002	.000	.000

a. Wilcoxon Signed Ranks Test

b. Based on negative ranks.

c. Based on positive ranks.

5.2 Summary of Simulation Results and Findings

The research summarizes the core research questions and results of the preceding statistical tests below in Table 5.80. We follow this summary with a case example to highlight these findings further.

Table 5.80 Summary of Experimental Results

Relationship and Research Question		Sig.
H1	Team size and average fitness and search times relate, $n \propto t_s, \overline{f_t}$	†††
	Probability of newcomers and average fitness and search times relate, $p \propto t_s, \overline{f_t}$	†††
	Propensity to repeat collaborations and average fitness and search times relate, $q \propto t_s, \overline{f_t}$	††
	Maximum downtime and average fitness and search time relate, $mdt \propto t_s, \overline{f_t}$	††
H2	Probability of a newcomers is inversely related to final fitness, $p \propto -{f_t}^2$	††
H3	Maximum allowable diversity is related to final design fitness, $m \propto f_t$	†††
H4	Maximum team-sizes exist for a given degree of complexity	†††
H5	Positive correlation ($\rho > 0$) between probability of newcomers (p) and both average fitness $\overline{(f_t)}$ and search times (t_s)	†††
H6	Negative correlation ($\rho < 0$) between propensity to repeat collaborations (q) and both average fitness $\overline{(f_t)}$ and search times (t_s)	††
H7	Positive correlation ($\rho > 0$) between the application of the Continuous Diversity Management Strategy (continually ramp diversity unless sufficient average fitness maintained) and final fitness values (f_t), negative correlation ($\rho < 0$) with search times (t_s)	†††
H8	Negative correlation ($\rho < 0$) between the maximum downtime (mdt) and search times (t_s), positive correlation ($\rho > 0$) with final fitness values (f_t)	†††
H9	Negative correlation ($\rho < 0$) between the baseline management pressure (λ_u) and search times (t_s), positive correlation ($\rho > 0$) with final fitness values (f_t)	†††
H10	Positive correlation ($\rho > 0$) between the application of the Consensus Management Strategy (continually ramp management pressure when sufficient average fitness maintained) and final fitness values (f_t), negative correlation ($\rho < 0$) with search times (t_s)	†††
H11	Positive correlation ($\rho > 0$) between the application of the Incremental Design Evolution (eliminate diversity when sufficient average design fitness found, no ramp) and final fitness values (f_t), negative correlation ($\rho < 0$) with search times (t_s)	†
H12	Negative correlation ($\rho < 0$) between landscape smoothness (S) and search times (t_s), positive correlation ($\rho > 0$) with final fitness values (f_t) when consensus required	†††
H13	Negative correlation ($\rho < 0$) between ideal design structuring [A^*] and search times (t_s), positive correlation ($\rho > 0$) with final fitness values (f_t) when consensus required	†††

††† Demonstrates statistical significance over a wide range of conditions
†† Demonstrates statistical significance over well-defined and restricted parameterizations
† Demonstrates marginal to no significance

5.3 Clarifying Case Application

The research now considers the faucet designs from Chapter 3 to provide a brief clarifying example. In this example, we consider each faucet design (the two-handle versus single-handle) as two distinct design approaches, each with their own corresponding fitness design landscape. We examine how a design management analyst may test design management strategies, while also comparing the likely outcomes between the two designs. For example, in the following case example a design management system may ask:

- Which design approach will reach market quickest (given alternative design concepts)?
- How many designers should I apply to the new product development effort?
- What design strategies should I employ to increase the design fitness and to decrease its time to market?
- How much should I encourage exploration versus exploitation of the design landscape?

Table 5.81 reproduces the associated design matrices for the faucet designs. This presented example and approach remains extensible to several other design examples (including software) and can easily use the outputs from well-known requirement applications, such as the IBM® Rational® DOORS® requirements management application or the Acclaro® DFSS requirements application. Table 5.82 captures the simulation setup for this case example, corresponding to the possible management system questions. This setup results in 2,400 simulations.

Table 5.81 C²D as a Design Comparison Tool and Framework

Two handle design N = 2, K = 1			Single handle design N = 2, K = 0		
	DP_1: Hot Water Valve	DP_2: Cold Water Valve		DP_1: Lever Up and Down	DP_2: Lever Side to Side
FR_1 – Controllable Flow Rate	X	X	FR_1 – Controllable Flow Rate	X	
FR_2 – Controllable Temperature	X	X	FR_2 – Controllable Temperature		X

Table 5.82 Behavior Space Implementation in Simulation for Case Example

n	["team-size" [3 1 6]]	mdt	["max-downtime" 40]
p	["prob_of_newcomer" 20 50 80]	Seed	["seed" random]
q	["prop_to_repeat" 85]	Strategy	["consensus_strat" true false]
m	["allowable_diversity" 50]	Fitness Goal	["stopping_fitness" 92]
N	["N" 2]	Repetitions	25
K	["K" 0] ["K" 1]	Commands	Setup, Go, Repeat

Table 5.83 Default Parameter Settings for Runs for Case Example

	Default Modelling Dynamics (Age?, Max-Downtime?, Hill-Climbing?, and Coalesce?)	On
	Require Same Stopping Point Strategy (Consensus)	On
Continuous Diversity Management Strategy	Pause and Restart Diversity Strategy	On*
	Dynamic Diversity Strategy	
	Stop Diversity if Average of the DAU is Fit Strategy	
Management Strategy for Consensus Building	Stop Prolonged Decision Making Strategy	On*
	Management Pressure (λ_u) Increase per Tick	0.030 dmnl

* *Turned on and off as a group per main hypothesis objective.*

After running the series of simulations, the analysis clusters the data into several different groups corresponding to the applications of strategy for each design landscape. This also includes splitting the data by the size of the design-team to understand the relationships, if any, between team-size and performance relative to the two design concepts. Although the specific case example is for a very small design landscape, the effects discussed represent statistically significant findings and relevant insights for the design management system. The results for these two designs under various scenarios follows in Table 5.84. Given real-world systems with several thousand requirements, often including a large number of interdependencies, these distinctions between performance values grow larger and more distinct.

Table 5.84 Simulated Performance for Two Design Concepts under Various Conditions

	Mean	Two handle design mean	Single handle design mean	Sign Test Sig.
No Diversity Strategies	Final fitness	.9945	.9996	.000
	Mean fitness	.5143	.8987	.000
	Search-Times	279.41	191.1333	.000

	Mean	Two handle design mean	Single handle design mean	Sign Test Sig.
Diversity Management Strategies	Final fitness	.9950	.9995	.000
	Mean fitness	.5499	.9069	.000
	Search-Times	321.51	235.40	.000

	Mean	Two handle design mean	Single handle design mean	Sign Test Sig.
Situational Management Strategies	Final fitness	.9953	.9992	.000
	Mean fitness	.5314	.8905	.000
	Search-Times	65.023	64.597	.000

	Mean	Two handle design mean	Single handle design mean	Sign Test Sig.
Both Management Strategies	Final fitness	.9950	.9996	.000
	Mean fitness	.5407	.8885	.000
	Search-Times	65.903	65.653	.000

The sample analysis shows that the most efficacious way for a design management system to limit the time to market is through the application of a situational management strategy, whereby technical leadership and management play a role in focusing and transitioning the efforts of the DAU from exploration to a mode of exploitation. Additionally, by splitting these data by team-size, the analysis found that having a team-size of four was optimal for the two handle design approach ($K = 1$), whereas a design-team of between four and five best met the time-to-market requirements in the case of the single handle design approach ($K = 0$). Given these findings, a design management system may decide to pursue a situational management strategy for the single handle design concept and allocate that design project a team of four design engineers. The success of this strategy requires a strong real-time performance evaluation system as the design progresses, and for the resource allocation within the entity to discriminate increasingly in its allocation of resources based on fitness differences between any design concepts.

Given the limited number of optima in the example, due to the relatively small design size, the fitness outcomes do not substantially benefit from diversity management approaches, *i.e.* the design approaches have relatively clear requirements and known relationships between variables. In more complex engineered design approaches this changes and diversity plays an increasingly important role, as highlighted in the hypotheses tested as part of Section 5.1. Discriminating the sensitivities of these variables over a wider range of scenarios forms the basis for future research. Nevertheless, the provided example highlights the types of questions that a management analysis can answer using the C^{2}D approach. In the following chapter, the research discusses additional future avenues for research as well as some final concluding thoughts.

5.4 Responsible Modelling Mechanisms for Results

The research now relates the modelling mechanisms described in Chapter 4 and their interactions to the results of the experiments. The following will discuss the hypotheses testing with regard to the dynamics depicted below in Figure 5.15. A full size diagram is included in Appendix AF.

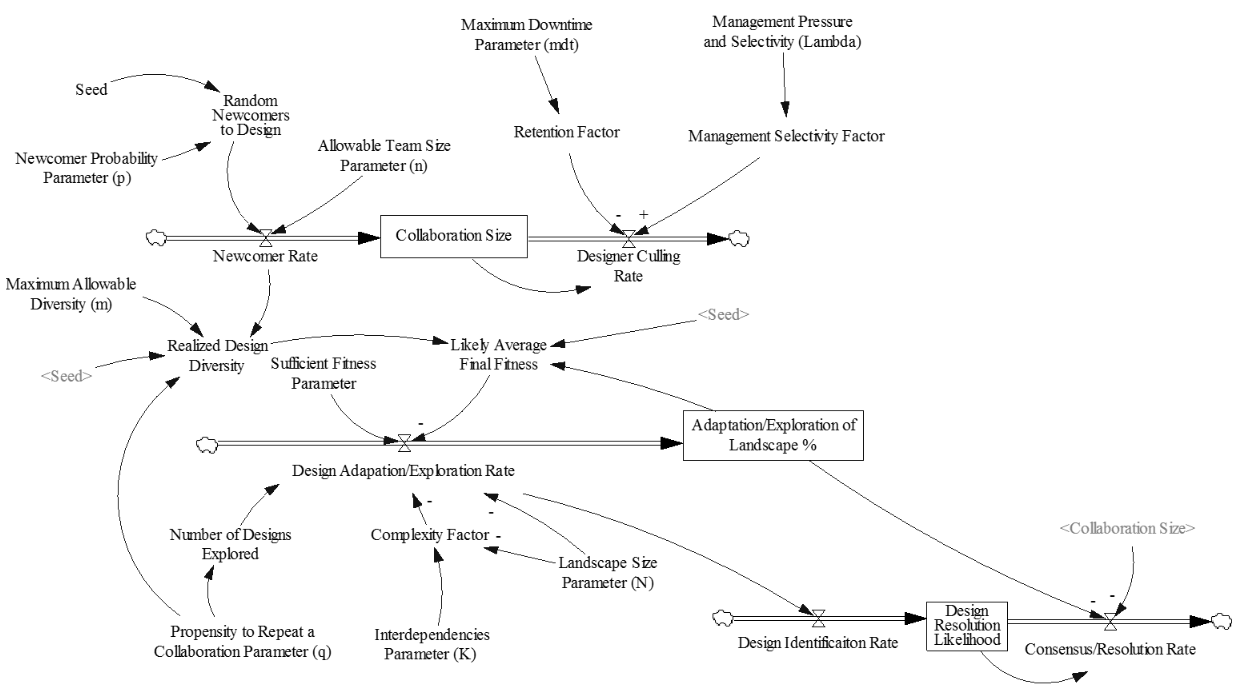


Figure 5.15 C^{2}D Dynamics Diagram for Discussion of Behaviors from Experimental Simulations

The research connects the modelling mechanisms from the previous hypotheses, as the testing of the hypotheses are meant to understand and test the expectations for the underlying model as opposed to validating existing empirical data. In fact, the value of the model as presented rests in its ability to generate new hypotheses and strategies to test. Future research aims to validate these models with empirical data collected from design collaborations. The following discussion allows the readers to understand the underlying mechanisms and dynamics of the model that are driving the results from the simulations discussed. The following sections connect the parameters used in the hypotheses tested above to the underlying simulation mechanics.

5.4.1 Team-Formation Parameters

Many of the key parameters tested in the simulations examined the relationships between the underlying team-parameters under inspections (i.e. the likelihood of incorporating a newcomer, propensity to repeat a collaboration, maximum downtime, team-size, and diversity) and the performance of the DAU in terms of fitness and search times. In the previous figure, we see that the interrelationships between these parameters and the underlying dynamics. Each of these factors correspond to the *Cgp* for Collaboration Dynamics, specifically mechanism $\mathrm{F}_{\mathrm{COL}_{01}}$discussed in Chapter 4, Section 4.2.5. These team-formation parameters and the underlying modelling structure relate to the results from the hypotheses testing:

- The newcomer probability has an influence both on the growth of the overall collaboration and the overall diversity of the DAU. With increased newcomers comes the ability to incorporate more diversity of thoughts and more ideas. Specifically, in the model this corresponds to the fact that newcomers enter the design space at a random location, whereas existing incumbents are limited to local optima accessible via hill climbing. Having an increased newcomer probability, given adequate diversity, results in the ability of the DAU to identify sufficiently fit design concepts by exploring a larger swath of the design-landscape. However, with all else equal, this benefit remains counterbalanced with respect to search-times as the diversity of design search locations increases, which raises the consensus time. This effect remains exaggerated for increasing levels of diversity, as on the average these increases results in the discovery of multiple sufficiently fit optima. The discovery of more optima similarly increases the number of alternatives for the DAU to consider in its consensus, which in turn increases the search-time. These counterbalancing forces leads to the inverse U relationship observed over certain ranges of the probability of newcomer in Hypothesis 2, as well as the statistically significant relationship to performance seen in Hypothesis 1.

- The maximum diversity parameter is a cofactor with newcomer probability. This parameter dictates the maximum distance from a recruiting designer (i.e. incumbent) that a new designer enters the design space. By increasing the allowable search area of a newcomer, the analysis shows a positive correlation to achieving a higher final fitness value as seen in Hypothesis 3. By altering the parameter to take on a dynamic range or to act as a switch between zero and a predefined value, the simulation is able to create strategies. This included the concept of Continuous Diversity Management Strategy in Hypothesis 7 and the Incremental Diversity Strategy in Hypothesis 11. In effect, these strategies create new feedback loops in the above figure, creating a feedback from the current fitness and a new formulation for the maximum diversity parameter.
- The team-size in the model also similarly represents a cofactor with the previous parameters. This team-size parameter accentuates the relationships established by the probability of incorporating a newcomer and the maximum diversity parameter. Having a larger team-size means that the collaboration reaches a larger number of ADMUs in equilibrium, given a realizable probability of newcomers.
- The maximum downtime parameter relates to the stabilization and equilibrium of the overall DAU collaboration. By increasing the parameter, the overall collaboration steady-state equilibrium also increases, with all else equal. As seen in the previous figure, this figure is one of the two factors responsible for controlling the outflow (i.e. culling) of designers from the collaboration. Hypothesis 8 found that the final fitness obtained remained positively correlated with this parameter and that the search times obtained remained similarly negatively correlated. In the model, the dynamic responsible for this largely stems from the fact that points on the landscape achieved by members of the DAU (including jumping-off points for newcomers) remain anchored longer. In other words, the local optima of the design landscape remain viable points to recruit from for longer. As a result, it takes less time probabilistically for the DAU to reach its final design concepts, as it does not have to readapt to a previously located design concept (a conceptual analogue

of picking up an old design concept from the shelf after already having partially explored its merits).

- The propensity to repeat a collaboration has a slightly different relationship to the performance of the DAU. Its effect is significant over certain parameter ranges as seen in Hypothesis 1. Over these ranges, its correlation remains negative with both the average fitness and the search times as seen in Hypothesis 6. However, its influence on the average fitness of the design time and its search-time occurs indirectly through its relationship to the cohesion and clustering of the DAU on the design landscape. In one sense, the propensity to repeat a collaboration represents a limitation on the internal diversity of the DAU, *i.e.* how well commonly one team member works with a new incumbent never previously worked with. As the propensity to repeat collaborations increases, so too do the relative number of clusters (i.e. design factions) of the DAU because of the fracturing within the collaboration. More directly, an increased propensity to repeat collaborations results in the formation of small isolated clusters of designers (i.e. design factions) who independently (separate graph) or semi-independently (loosely connected) explore the landscape. Because of multiple design loci existing across multiple suboptimal design concepts for longer, the average fitness decreases; however, with these multiple design factions formed, the recruitment of newcomers occurs radially out from each of these locations, resulting in a quicker discovery of a final design concept.
    - The adaption of the propensity to repeat a collaboration parameter to this framework highlights a key distinction from the work of Guimerà et al. (2005). In the work from Guimerà et al. (2005) the propensity to repeat a collaboration was the only mechanism through which diversity was evaluated, *i.e.* as propensity to repeat existing collaborations went up the diversity of the collaboration was through to go down. In the C^2D model, these isolated groups similarly represent less internal diversity in the sense of their team composition; however, the distinction is that they conversely provide, on an existential level, the DAU unique perspectives as they represent different feasible design approaches. The balancing of the propensity to repeat collaborations against the need to form well-connected and diverse teams remains an area for ongoing and future research, especially in its reconciliation with the dynamics implemented within the C^2D framework.

5.4.2 Design-landscape Parameters

Many of the remaining factors tested in the simulations included lands-scape related factors and their relationships to the performance of the DAU in terms of fitness and search times. In the previous figure, we also see the interrelationships between these parameters and the underlying dynamics through the landscape size N and the interdependencies K. Each of these factors correspond to the *Cgp* for the Simulation Design Landscape, specifically mechanism $\mathrm{F}_{\mathrm{LND}_{02}}$ discusses the size of the landscape parameter and the interdependency of the landscape parameter (an alternative representation of Smoothness similarly follows in $\mathrm{F}_{\mathrm{LND}_{03}}$) as discussed in Chapter 4, Section 4.2.2. These design landscape parameters and the underlying modelling structure relate to the results from the hypotheses testing as follow:

- As the size of the landscape increases, the time it takes the DAU to locate sufficiently fit design concepts also increases. However, this increase follows a linear progression given no corresponding increase to the level of design interdependency.
- The degree of interdependencies relative to the size of the landscape provides a measure of complexity for the design approach, which we inversely discuss in terms of the landscape smoothness in Hypothesis 12. In Hypothesis 12, the analysis found a negative correlation between the smoothness search time and smoothness and a positive correlation between smoothness and the final fitness values of the DAU. In an ideal design case, discussed in Hypothesis 13, the analysis similarly found that an ideal design structure (one with complete smoothness) provided the same correlations. The mechanism responsible for these relationships stems from the fact that with increased interdependencies relative to the size of the design landscape there is an increasing number of local optima of insufficient design fitness. In other words, the DAU increasingly has to sort through multiple design locations before locating and adapting to a sufficiently fit design location. In very rugged landscapes, the DAU quickly adopts to one of the many local optima. However, most of these local optima represent insufficiently fit design solutions. This results in the logarithmic relationship between increased interdependencies and search times. Ultimately, this manifests in the overall system dynamics pictures in the above figure through the rate of adaption or exploration of the DAU.

6

CONCLUSION AND DISCUSSION

"Any fool can make things bigger, more complex, and more violent. It takes a touch of genius-and a lot of courage-to move in the opposite direction."

- Albert Einstein

The endeavor of engineering design has since time immemorial dealt with issues of complexity and unexpected behaviors; designers, in one form or another, often provide the initial scouting parties for theoreticians and experimentalists, responsible for charting the boundaries and practicalities of both new and old discoveries alike, both through their successes and failures. Take for instance the Dialogues Concerning Two New Sciences by Galileo Galilei (1638), specifically the portion where Galileo describes how masons during their typical practice would lay out large marble cylinder columns so that each of their ends rested upon separate support beams. The discourse goes on to describe how a mechanic, out of a dose of extra precaution, changes that design to add a third support column in the middle to be doubly sure the supported marble column remained intact. Yet, despite the common expectation shared among the workers that this precaution seemed opportune, the result was that within a short period the marble column cracked directly above this new middle support. Johnson (2006) points out the discovery of this unexpected crack represents an early example of the manifestation of elegant complexity, one where the underlying physical relationships, once understood, would offer a simple answer to a complex question. However, since these early forms of complexity, the design of modern engineered systems progressively represents an increasingly 'messy' if not 'wicked' problem space, comprised of many interconnected socio-technical design issues and possibilities for unintended and unanticipated emergent behaviors. The introduction of the research in Chapter 1 set the stage for the conversation by providing an overview of the potential negative consequences of this unintended form of design complexity.

Increasingly the challenges of design involve not only the resolution of technical challenges, but overcoming difficulties for design management systems in maintaining and ensuring the proper coordination of agents (i.e. designers) and allocation of resources. The design of engineered systems today often require the coordination of hundreds to thousands of engineering design participants who span multiple organizations, disciplines, companies, and geographic locations, which results in a highly dynamic and complex collaborative network. Although the literature supports multiple interpretations of complexity, and of engineering design, this work specifically, in summary, defined complexity as the relative number of interdependencies in a design to its size and engineering design as a decision-making process for exploring the design possibility space. The purpose of this research was to respond to a related and underlying motivation - to explore how engineering design management systems can best enable their enterprises to succeed in the midst of a growing degree of both technical and socio-technical complexity. The central research focus of this exploration discussed in Chapter 1 included:

- How does the complexity of design artefacts relate to the performance (expressed as a fitness values on the design landscape) of collaborative design teams?
- What factors inherent to design teams and the dynamics surrounding their formation, in terms of their internal collaborations or associations, suggest strategies that mitigate the influences of design complexity?

6.1 Contribution to the Field

In order to respond to these original questions, the research provides a framework rooted in the literature for exploring these questions, the *Complex Adaptive Performance Evaluation Model for Collaborative Design (CAPEMCD or C^2D)*. The framework as a result represents a fusion of well-validated conceptual elements and brings together distinct research efforts. As part of establishing this framework, the research surveyed a wide range of theoretical issues surrounding design complexity, design-teams, and design performance. Most predominately, the established framework builds upon the following research summarized in Chapter 2:

- Principles of design from the Axiomatic Design approach established by Suh (1990);
- Fitness landscape representations for the adaption of a species described by Wright (1932) and as later adapted in the tunable rugged NK landscape model by Kauffman (1989); and,
    - As part of this representation, we adapt the Axiomatic framework from Suh (1990) to represent functional requirements as genetic components with design parameters as fitness components.
- Team-formation parameters and their relationship to team-performance as discussed by Guimerà, Uzzi, Spira, and Amaral (2005)

The contributions from this research, discussed in Chapter 3, that make the final C^2D model possible include:

- A methodological approach that links the number and the interdependencies of design elements (i.e. requirements and design-parameters) as a means to create a design fitness landscape representation of design complexity; and,
- Introduction of the Designer-Artefact-User (DAU) system and its Agent-Based Decision-Making Units (ADMUS) that transverse on the design landscape, including:
    - The explicit relationship between the diversity (m) of these agents and their locations on the design landscape measured using distances (i.e. patches) in the model;
    - The implementation of team-formation parameters (n, p, q, mdt, λ_u);
    - The ability to capture performance (i.e. fitness and search-time) of the DAU and the characteristics of its collaborative network (e.g. percentage of newcomers, degree of cohesiveness); and,
    - The implementation of design strategies that guide the movements of the DAU on the landscape and to control the growth of the collaborations

The research as a whole contributes to the literature by providing a method for examining the performance of engineering designers through a socio-technical lens, which combines aspects of team performance and the underlying technical complexity of an engineering artefact. This contribution required the bridging of several key concepts and principles from the multiple highlighted domains. This bridging included: 1) adapting the design-structure matrix (DSM) approach and principles inherent in the Axiomatic Design domain, 2) utilizing the metaphor of fitness landscape and the DSM to create a compact representation of design fitness and complexity, and 3) applying complex adaptive systems (CAS) thinking to the DAU and the design ADMU. The contributions of this research to the field of engineering design science and performance evaluation begin by providing the essential building blocks necessary to examine and strengthen the linkages between the socio-technical aspects of design. This examination includes linking the team-dynamics and performance of design teams and the complexity of underlying engineering design approaches. The research represents the underlying complexity of the design approach by virtue of the ruggedness of the design landscape and captures design performance characteristics using simulated fitness values from the design landscape. In evaluating design performance, this research adopts an objective function of minimizing design times while simultaneously having to meet the constraint of a minimum sufficient fitness value, equivalent to the need to achieve a minimum design valuation. Although future research considers alternative performance metrics, this original bridging focused on the performance outcomes of an engineering design process most relevant in the instance of new product developments. Another important contribution resulting from this overall research examination is that it enables design management analysts to develop, test, and communicate various design management strategies (e.g. explore early and exploiting late, limit newcomers) against approximate design approaches (e.g. highly complex design landscapes).

Through this initial work, the research has shown that a group of autonomous ADMU agents, driven through a set of simple search and team-formation rules, can represent a DAU management system. Similarly, the research has shown that this approach provides an insightful framework for evaluating the progression of these collaborative agents as a design effort progresses from its start to its conclusion: the selection of a final design concept. To facilitate comparative research with similar research projects at the System Performance Laboratory and continued research with the CAS ABM community, the research in Chapter 4 presents the C^2D model using the language of emergence, the Constrained Generating Procedure (*Cgp)* notation from Holland (1999). As part of this, the research has identified the overall *Cgp* mechanisms for the C^2D simulation, including the subordinate mechanisms governing the user interface, the design landscape, the simulation environment, the ADMUs, the collaboration dynamics of the ADMUs, and the design strategies of the ADMUs. By implementing these mechanisms via the coded functions in NetLogo, the research provides an operational C^2D CAS ABM simulation model.

This operational model enabled the research to conduct a full factorial design of experiments to examine the simulated effects of various design parameters on the performance of the DAU as part of Chapter 5. These experiments tested for the emergence of beneficial DAU behaviors during their design activities. In the model, the examined phases of design activities generally track to the exploration of design concepts (i.e. movement across the design landscape), the time spent reworking design approaches (i.e. the change of one design locus to another), and the time spent converging on one design approach from multiple potential design solutions (i.e. time spent in a consensus building process). The results of this analysis demonstrate that the collective behaviors of the ADMUs under specific and relatively simple design strategies (e.g. increasing exploration early in the design process) can result in patterns of beneficial behaviors that lead to increasing levels of design fitness (both with regard to average and final values) and decreasing search-times. These simulation results suggest that the C^2D model remains capable of generating policy options (e.g. encouraging hiring of designers early in the process, increasing selectivity of design approaches after the discovery of a likely feasible design option) to real-word design management systems not previously considered. Moreover, the developed model promotes the consideration of policy options that recognize socio-technical factors, extending beyond just the structural complexity of a design approach commonly referenced in the literature.

Finally, the resulting simulation model and framework discussed provides a basis for the ongoing generation of hypotheses and new questions. This overall approach enables future research to continually develop and test new strategies through the extension or use of the existing framework. The following sections of this chapter summarize key insights developed from the construction of the described C^2D framework relevant to the DAU management system. Additionally, the research similarly reviews highlighted areas for continued exploration in the future. The goal is that these continued explorations would result in both a strengthened conceptual baseline (e.g. inclusion of the preferences of designers) and further translational work for this framework into other domains within and outside of engineering design.

6.2 Generalization of Insights

In Chapter 5, the analysis looked for emergence by examining that data for repeated patterns of behaviors over multiple thousands of simulations. During this analysis, the simulations revealed that the use of certain design strategies, specifically those managing the diversity of design-teams and the involvement of management, result in beneficial performance outcomes for the DAU. However, of interest beyond specific investigations and findings is not only the discovery of unexpected behaviors from single tests or how well the simulations conformed to the expectations of the modeler (i.e. to the research hypotheses), but rather the unexpected general heuristic potential of the approach, *i.e.* how well the framework effectively provides a mechanisms for generating and generalizing insights.

Along this vein, the research and its discussions have demonstrated that the engineering design process represents a form of a highly messy, if not, in some instances, a characteristically wicked problem. Moreover, the research has shown that the engineering design process, when faced with even a relatively small number of interdependencies, is extremely difficult - design solutions do not simply result from repeatable, well-defined, or sequential processes. Engineering design represents a creative process that exponentially increases in coordination costs with growing complexity. This, however, does not mean that engineering design should abandon process; it simply means that the successful DAU management system must actively use a series of strategies to help the process successfully achieve organizational objectives. At its most fundamental level, the research has shown:

- Engineering design requires the careful development and active management of dynamic and adaptable teams – the design of complex systems requires high performing collaborative teams that explore the design landscape together, realizing fitness goals faster.
- Reduction of structural design complexity remains only one element in improving design performance. More simply, although past techno-centric approaches remain important, continued improvements of the capacity for design management systems to overcome complexity requires new socio-technical methods that consider both the designer and user, as well the artefact.
- Design teams are multidisciplinary and as the demands of the team change over the course of a design, so too must the characteristics of the design team change. Tested design strategies that manage the "diversity" of the design-team demonstrate this need conceptually. The analysis demonstrates that more diversity (to a point) results in statistically significant improvements to the final design concepts (i.e. final fitness

locations). Moreover, successful designs and design management strategies encourage the inclusion of diverse viewpoints during its formative activities.

- Engineering design management systems must remain actively engaged in the design process and be able to step in and drive competing design approaches to unity when required in a given design process. This requires the management system maintain a set of well-defined percepts to aid the management system and its strategies, in the case of the model this means that management system must have adequate and accurate reporting structures to remain aware of the average design fitness and design search-time. In the analysis, the tested rules and active management strategies demonstrate the importance of increasing the selectivity (i.e. reluctance of the DAU to further develop alternative design concepts) of the management system under certain conditions.

The discussed insights highlight the importance of design management strategies in incentivizing the DAU to reach design objectives. The most important aspects in making the tested strategies successful included enabling designers to explore competing design concepts, allowing designers to collaborate in the selection of a final design concept, and, finally, the presence of a management and technical-leadership, responsible for resource allocation, pressure to drive the alternative design concepts, and the collaboration to consensus. These concepts involve:

- Collaboration (creative process) – The formation of DAU design-teams results in the collaborative exploration of the design space. This design exploration includes a creative process of evaluation, analysis, and synthesis. During this process, each design-team and its members explore sections of the conceptual design landscape that, conceptually, best aligns with its preferences and experiences. These dynamics help to locate feasible design solutions. However, the selection of one of these identified solutions over another requires the concepts of competition.
- Competition (convergence) – Following the exploration activities, the design-teams must converge on a design solution. The natural selection metaphor from natural systems provides the dependency resolution strategy and mechanism to promote convergence. This selection dynamic provides a degree of competition in a design collaboration. This dynamic provides the essential mechanism through which opposing design alternatives emerge and, based on their relative merits, gain prominence. In this construct, the management and

leadership pressure provides the degree of selectivity in the dynamic. The greater the involvement of resource holders, the more important the differences in the merits between design concepts becomes.

- Strategic Selectivity of the Resource Holder (rework and consensus) - In essence, by allowing relatively underperforming design concepts to continue until a point (i.e. until the average of the collaboration found a fit concept), a healthy section of the design possibility remains revealed. For example, a design collaboration may explore several design concepts of various merits before any gains prominence through the competitive process highlighted above. However, sometimes factions of relatively similar merits can develop. In these instances, management can help bring the DAU to consensus by steadily increasing its selectivity. This process also mirrors a process of rework, where gradually the DAU resolves errors in their original understanding of the shared objectives of the design. The increase in selectivity of management limits the likelihood of less fit design concepts to out-compete for resources, *i.e.* new designers. This means increasing scrutiny of resource requests for competing design concepts and requiring each design faction to provide increasing levels of justification for resources. Eventually, this approach reduces competing and alternative design viewpoints, and increasingly drives the design to resolution.

The remaining discussion highlights specifics relating to insights specific to the parameters and dynamics explored in the model, the design landscape, and thoughts regarding the use of design strategies.

6.2.1 The DAU and Its Parameters

During the previous analytical work of Chapter 5, the research explored each of the design-team formation parameters. The research pursued the design-team focus along with its behaviors over time as an attempt to explore alternative techniques over existing, often rigid and static, design management tools, which commonly neglect the role of the human designer and human user of engineered systems. As processes have become more complex, design teams (not individual designers) have become the basic working unit in most modern engineering design organizations. We used these design-team parameters as an initial starting point for this exploration. In the model, these parameters govern how actors (*e.g.* designers, managers, users), each playing different roles in the design process, come together to form a self-regulating socio-technical system entity, the DAU. As part of this analysis, the research generated a number of unique insights about how these parameters can help to positively influence design outcomes. The most prominent insights included:

- The optimum team-size, based on the assessment of productivity, is one that matches the team-size, in general, to the complexity of the design tasks with a team-size centered around seven. For highly complex design tasks, a team-size of four proved ideal while for designs with relatively low complexity a team-size of nine proved ideal. For the design management system, this insight suggests that by taking into account design complexity the DAU can improve design performance by assigning appropriately sized design-teams.
- The probability of incorporating a newcomer together with the maximum allowable diversity of the design-team and propensity for repeating collaborations formed a diversity potential for the DAU that influences the final fitness of design concepts. However, the increase in diversity can cost the DAU in terms of time to market. In general, when looking at overall fitness relative to search times, successful design teams (i.e. achieving time market objectives) incorporated a higher fraction of incumbents (i.e. $1 - p > 50\%$) which suggests that expertise and knowledge enabled the design teams to be more effective in their design activities. Similarly, having a higher propensity of repeating collaborations limited the effectiveness of diversity, and as a result hampering the ability of the design team to achieve the same relative success. What this means for the design management system is that the management of teams and their diversity can lead to improved design outcomes.
    - What the analysis revealed is that the benefits of having increased diversity in the general exploration of the landscape asymptomatically reaches a limit at approximately 22% of the maximum diversity (i.e. the diagonal or the maximum distance from one point to another on the landscape), even on very rugged landscapes. What this means for the DAU management system is that design strategies can improve by selectively incentivizing reasonable degrees of diversity on design teams, *i.e.* a level that corresponds to the asymptotic limitation. How can a design management system implement this in reality depends on future

translational research; however, one can imagine for instance examining similarities based on professional background, education (e.g. technical vs. non-technical), level of educational achievement, life style, geographic original, and even factors such as religions, beliefs, and values. This insight covers aspects of 'how much,' but 'how often' is another, yet related, question regarding the likelihood of incorporating a newcomer.

  - How often a DAU should incorporate this level of diversity remains a less straightforward answer. With a limited probability, as the relatively few newcomers enter a design collaboration at first their contributions remain minimal, so the DAU quickly finds local optima independent of their contribution. For example, the search vicinity of the DAU as a result generally remains confined to the local neighborhood of the incumbent design collaboration, resulting in short design time but less than optimal design fitness outcomes. However, with too many newcomers joining the collaboration, the collaboration becomes unstable, *i.e.* it remains scattered and spends more time locating and resolving design concepts with little to no gains in fitness. In general, the research showed that having design teams of 20 to 45% newcomers provided the best design outcomes in terms of search times.

- A perhaps surprising finding was that the maximum-downtime of a collaboration was significantly important in both reducing the time to market (i.e. search-times) as well as increasing final fitness. For the design management system, this highlights the importance of retention of designers. When combined with strategies to remove low performing design concepts from the collaboration, it becomes even more important to retain collaborators longer.

6.2.2 THE DESIGN LANDSCAPE

Similarly, the research and its analysis previously explored the factors responsible for generating the design landscape. The design landscape takes on the characteristic of fitness landscapes from biology, and relates the requirements of a design to the genetic characteristics of a biological entity (e.g. the potential of a biological entity). In these biological fitness landscapes, the presence of one or more gene can often interact with a gene and, as a result, influence its fitness through a shared fitness component. Similarly, using synectics, the analogy to design relates fitness components of a biological entity (e.g. performance characteristics likely to increase the success of an entity to impart genetic information) to the design parameters of an engineering design. This initial framework only considers the binary possibility of the design parameter existing or not existing using the NK framework from Kauffman (1993). This approach allows us to abstract design complexity for purposes of design planning. Using this framework and resulting model, the analysis provided a number of unique insights. The most prominent insights included:

- The size of the landscape tracts linearly with increased search-times, whereas interdependencies and complexity (i.e. the density local optima) cause search-times to escalate exponentially.
- It is the purpose of the design process to explore the design landscape; however, with more complexity there is an increasing degree of possible design solutions of varying levels of fitness, attracting and growing design contingencies. In these instances, the active involvement of design strategies and management becomes increasingly important in quickly failing and discovering a workable design, *i.e.* letting go of poor concepts in favor of great ones.
- Strictly adhering to the rules of axiomatic design results by definition in a maximally smooth design landscape, which supports findings from literature that aim to reduce structural complexity.
    - However, even ideal and well-designed systems often include some degree of complexity. Sometimes this is the result of the natural process of incorporating modular systems, and in so doing inheriting existing, interdependencies, and in other instances it is the outcome of unanticipated usages of an artefact by the user that introduce new interdependencies that affect the functioning of an engineered system.
    - It is clear that the design landscape is dynamic and ever changing, in which design benefits most from the incorporation of design rules and strategies that incentivize beneficial patterns of behaviors but that do not dictate top-down courses of actions.

6.2.3 *Design Strategies*

Perhaps one of the most important outcomes from the research centers in the realization that successful design management systems are not only important but are required for the success of any engineering design effort. As seen throughout the discussions in this dissertation, engineering design remains riddled with complexity and interdependencies. These engineered systems represent more than gadgets but rather form a holistic socio-technical system, which must meet the need of the user in its intended context. Design processes are messy and driven by the behaviors of the human designers and users at the heart of the practice.

To improve design performance beyond its current state, the subtle yet important socio-factors of teams and collaborations must help reshape and reinforce current design theory. This work does not advocate advancing socio-technical systems engineering approaches at the at the expense of the preceding technical foundations of design science. However, the future success of design efforts depends on the ability of its management systems to incorporate a wider perspective of design, especially when it comes to effectively mitigating the increasingly complex design requirements faced by the design community. Current approaches to managing design often lead to incrementally driven approaches, which, although useful, carry limitations and legacy overhang that restrict the exploration of radically innovative positions on the design landscape. As the number of interdependencies in design grow, deformations to the design landscape may eventual require even currently acceptable design to similarly seek on radical new locations on the design landscape. Exploring these new positions on the landscape means not only pushing the boundaries of technological and scientific feasibility, but also establishing systems of incentives that allow for the organic and appropriate coordination of designer-designer, designer-organization, designer-process, and designer-user interactions and needs. In order to make complex design requirement elegant and their solutions simple, engineering design must look to socio-technical design management strategies to accomplish these goals as highlighted in Table 6.1.

Table 6.1 Levers of Successful Design Strategies for Design Management Systems

	Grow the Collaboration	**Focus the Collaboration**
Key C^{2}D Parameter(s)	more p, n, mdt	less p, n, mdt
Design phase	early	late
Design complexity K	small K (rugged landscape)*	K (rugged landscape)*
Technology change rate	static landscape	dynamic landscape

	Limit Diversity on Teams (Design Exploitation)	**Encourage Diversity on Teams (Design Exploration)**
Key C^{2}D Parameter(s)	less $m, p, 1/q$	more $m, p, 1/q$
Design phase	late	early
Design landscape K	small K (smooth landscape)	large K (rugged landscape)
Technology change rate	static landscape	dynamic landscape

	More Management Selectivity (Less Risk Taking)	**Less Management Selectivity (More Risk Taking)**
Key C^{2}D Parameter(s)	more λ	less λ
Design phase	late	early
Design landscape K	small K (smooth landscape)	large K (rugged landscape)
Technology change rate	static landscape	dynamic landscape

*When it comes to how much to search (especially with regard to finding an improved maximum fitness location), a DAU generally improves through a larger collaboration. However, when factoring in time and consensus the research shows that this archetypal strategy requires alteration. For maximally complex design landscapes, the research suggests that search by small design teams (from four to seven in size) achieves the best overall performance when design time remains a consideration.

Although the research at times has used the term “the designer,” we do so with the understanding that design occurs in the context of the endeavor of a complex socio-technical system, the DAU. This system is responsible for managing teams of designers and, in many cases embedded users, with interacting specialties, disciplines, requirements, and preferences. By including complex system scientists as the analysts, the design and implementation of policy-directed strategies can guide the DAU through all stages of the design process. However, the C^2D approach provides only an initial framework for testing and developing specific policies. The inclusion of new parameters and techniques can greatly enhance future research.

Although many findings from the research remain generally academic in orientation, the associations, related implications, and possibilities for implementation in real-world design management systems are great. With regard to implementation, additional translational research will help to discern further ways to incentivize the beneficial patterns of design behaviors discovered using the C^2D model. This C^2D model ultimately provides a design performance framework, through its simulated fitness values on the design landscape, for:

- exploring divergent problem exploration through the agent-based search of the design agents;
- the structuring of a problem through the design landscape; and,
- the convergence on a solution through the consensus activities of the DAU and its analogy to natural selection processes.

Ultimately, the appropriate design framework depends on the design situation and the strengths and weaknesses of the individual design teams. Nevertheless, the value of the presented C^2D framework is derived foremost in its ability to test design strategies, which are in essence a set of intended actions for designers to follow (rules at the bottom-up level) and possible management control functions through collective rules and management practices (at the top-down level). In the CAS based framework, these strategies rely heavily on the concept of incorporating incentives to improve design performance. To implement these incentives in practice will require design management systems to amend or replace traditional design process methods and management tools with new approaches that explicitly measure and focus on complex environmental and socio-technical factors. For example, design management systems should consider the trade-off processes inherent among designers as a form of negotiation and explore the use of incentives (e.g., allocation of resources, bonuses, access to additional personnel) to resolve negotiations in ways that ultimately align design-trades to the organizational design objectives. Even when pushing decision making to the lowest possible level and across multiple small teams, the challenge remains in how to coordinate these teams and ensure that they do not work at cross-purposes. The management challenge requires setting up incentive structures to ensure that integration across teams occurs naturally and at the speed of necessity, as it remains impractical and sometimes impossible, due to the sheer number of required decisions, for a single decision making entity to intervene on each decision and technical trade in a design effort. As pointed out, these new tools requires design and management processes to consider decision rules and strategies, the nature of incentives and negotiation in design teams and organizations, the role of the designer and its interactions, the role of self-organization, and, ultimately, the possibility of manufacturing beneficial emergence. The resulting new design management techniques may also as a result help to avoid system lock-in design events, premature convergences on design approaches, or competency traps that lead to limited exploration of the design landscape.

6.3 Research Constraints and Future Opportunities

The research has shown that design is a complex socio-technical process navigating the complex relationships between a design problem and a set of potential design solutions. However, to limit the scope of the research and to focus on assembling the foundational elements of future research, we deliberately constrained the research in a number of important ways. This included the application of constraints both in the construction of the complexity representation, the design landscape, and in the examined socio-technical factors:

- Design Landscape C^2D Representation – The research restricted the relationship between the problem and solution through the incorporation of a fitness landscape. Although design more aptly represents a coevolution between the problem and solution, the presented research only pursued questions regarding a static design landscape representation. However, the design landscape as implemented in the model provides the opportunity to consider dynamic changes. Additionally, the design landscape only represents an approximation of the complexity through the NK landscape. As a result, the landscape represents the physical nature of the underlying engineering artefact, while not explicitly incorporating economic, market, legislative, and regulatory constraints.
- Design-Team C^2D Representation – The research restricted its attention to a few parameters shown in the literature to have high explanatory value, specifically restricting the majority of testing to strategies and parameterizations concerning the team-formation

and assembly dynamics of collaborative teams. The representation of the designer and user remained indifferent towards any unique designer preferences or designer differences.

Further, the discussion of engineering design and design-team performance primarily relied on understanding the designer-designer interactions within the DAU as they explored the design landscape. These constraints provided the necessary boundaries for the completion of the initial research performed as part of this dissertation; however, the research remains an ongoing research endeavor to understand both the role of complexity on design performance and how to promote beneficial forms of emergence to improve the performance of design teams. Further developing and maturing the C^2D requires continued translational work.

Beyond increasing the sophistication of the C^2D model and its underlying methods, the primary thrust of our future research will be to conduct field experiments using the existing method laid out in the research. By taking empirical data from engineering projects[47] and applying the developed method, the research will validate the essential conceptual elements of the model. It is essential that we link the simulation platform developed to real world experimentation. Although complex adaptive systems agent based modelling and complex ecosystem metaphors have been applied to decision-making in a variety of fields[48], the meaning of "validation" in the context of the complex adaptive systems and agent-based modelling is itself not well understood (Gilbert 2008). Moving forward in the immediate term validation for the C^2D effort will encompass the comparison of aggregate results from simulations versus collected data where possible. With the initial linkages between engineering design, team-dynamics, complex adaptive systems, socio-technical systems, and design performance formed as part of the research, we are ready to engage the research with real world design problems.

Additional future research directions include maturing the C^2D framework, in particular, this involves the execution of additional experiments to further isolate, confirm, and characterize the emergent behaviors seen in the model. Further, this involves solidifying the identified conceptual linkages between research domains into an increasingly parsimonious representation. Part of this

[47] Common requirements and project management programs have suitable files for such continued translational research. Such programs include, but are not limited to, Microsoft® Project®, IBM® Rational® DOORS®, and Acclaro® DFSS.
[48] Fields include healthcare (Kernick 2002), manufacturing (Nilsson and Darley 2006), economics (Beinhocker 2007), and sociology (Sawyer 2005), among others.

effort may include the comparison of the C^2D approach with other tools for descriptive dynamics, such as exploring further top-down system dynamics modelling representations of the concepts explored as part of this research. Continued research will expand the reach of the framework presented to a broader range of research questions and, in so doing, increase the overall applicability of this research in a number of important ways. These important ways concern not only improving the performance of design-teams, but also in researching ways to incentivize design management systems and environments that allow the DAU socio-technical systems to create more resilient and ultimately successfully engineered systems. Some of the remaining research application venues and particular avenues for continued research follow below.

6.3.2 APPLICATIONS TO RESILIENCY

Future and ongoing research looks at ways to embed resiliency in the design of systems to overcome and even incentivize positive forms of emergent behaviors, leading to virtuous performance dynamics for the system. Each of the particular events and examples from the implementation of the systems engineering process represent failures of large socio-technical systems and highlights the capacity of complex modern engineered systems to fail and, as a result, gravely harm the public and society. However, instead of focusing on eliminating emergence, another approach is to find ways to incentivize positive forms of emergence that could allow systems to respond, recover, and operate through system or subsystem failures. Part of this requires incorporating improved models of designer preferences and the fitness landscape.

6.3.3 DESIGNER PREFERENCES

As part of the C^2D implementation in this dissertation, we assumed that each designer operates with respect to a shared understanding of the fitness F_i. However, we include the possibility of heterogeneous preferences as an area central for future research. For example, members of the DAU more accurately represent various communities with their own design preferences. Design as a result represents a coevolution of these communities. As part of our recommendations for continued research, we propose representing these differences through coevolving fitness functions for the individual design communities. As a result, the adaptive movements of one design community can influence and drastically change the fitness landscape for another design constituency at each increment of time. For example, increases in the thermal budget on a design for a spacecraft can drastically improve or limit the available options for a battery or propulsion subsystem designer. We can theoretically account for these differences through the incorporation of a coevolution dynamic. Future efforts could expand upon these relationships by allowing multiple designer types (e.g. subsystem representations) each with their own unique fitness landscape. Although we currently envision treating the design landscape as a shared fitness landscape by each of the designers, where the movements of one designer affects the fitness model and the resulting fitness landscape representation.

6.3.4 *Alternative Representations of the Landscape*

The current NK representation of the design fitness landscape provides a limited approximation of the role of complexity on the resulting fitness of a design. An improvement to the model may include the use of a more specific landscape representation of design complexity and design performance, based on the actual underlying physical performance characteristics of a design. This is possible using weights for each of the interactions between a requirement and design parameter. More specifically, the sensitivity of change in the performance of the functional requirement as it relates to the design parameter can serve as such a weight. Aside from the possibility of adding weights to the existing fitness function approach, an alternative to the fitness landscape all together could rely on using alternative representation, such as Boolean network representations that similarly represent the interconnectedness and size of a state space.

6.3.5 *Strategy and Mechanism Design*

In future work, we foresee using the experimental findings and empirical data to refine, develop, and create strategies to develop general performance incentivizing strategies centered on leveraging socio-technical factors beyond just the growth and diversity of design collaborations. Further, we could introduce observed data or trends in lieu of making these parameter experimental variables. These improvements could further promote and aid the ability of the design management system to ensure that the DAU achieves its goals both efficiently and effectively.

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APPENDICES

APPENDIX A: THE EDGE OF CHAOS IN DESIGN

Phase transition is a term used in physics and the sciences to describe the threshold where matter changes states. At this point, a system becomes dynamic and unstable. In our relationship of design to the concepts of complex systems, we envision a point of maximal complexity between order and chaos. Research in complex adaptive systems refers to this point as the edge of chaos and describes it as an enabling condition for the perpetual novelty or evolution of systems (Langton 1990; Crutchfield 2002). We envision this point as applying both to the structure of the designer-artefact-user (DAU) system in its exploration for design fitness, as well as to the engineering artefact and its performance. In the case of a highly collaborative DAU, the self-organizing and interacting design community it represents can give rise to a balance between order and disorder in the design space. From a market perspective, this point can refer to, in the case of design, a point with maximum number of features and their interacting dependencies without a system losing value (e.g. time to market). As an example, Kuwabara (2000) refers to the highly successful and collaborative Linux platform and its development as a "bazaar at the edge of chaos" because of its balanced approach towards exploration and exploitation, resulting from its nature of being an open source development effort and the application of structured restrictions or rules on its contributors.

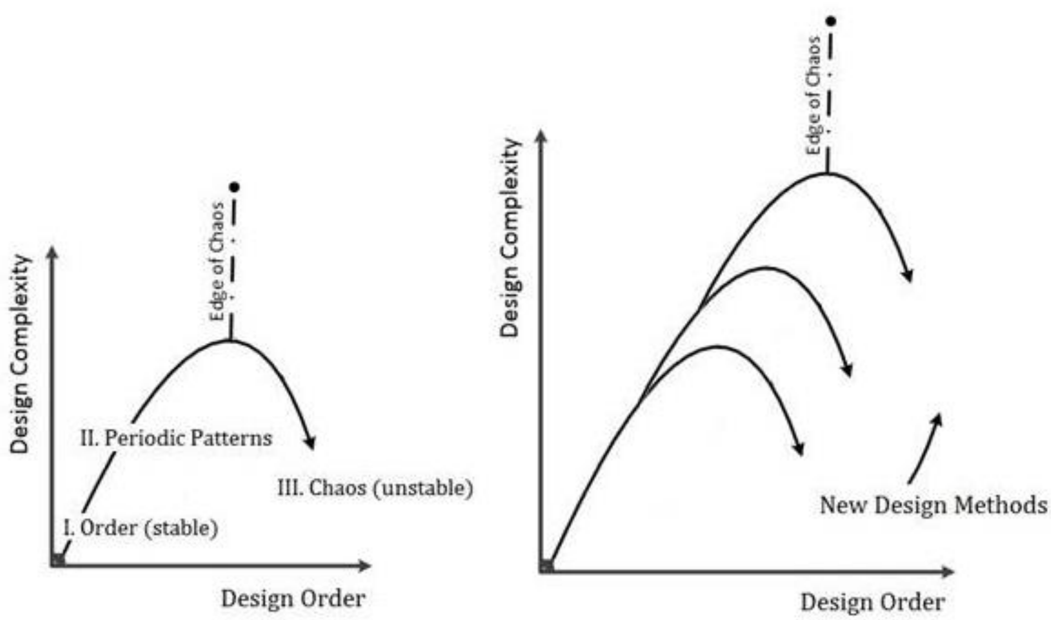


Figure A.1 Design Complexity as a Balance between Order and Chaos. This research hopes to enable continued research in this domain to identify new methods to allow designers to not only cope with complexity but to overcome its ceiling.

Appendix B: Mission Cost of NASA Mission Systems

Table B.1 Space Mission Cost Data

Mission	Launch Annum	Planned Cost ($M)	Final Cost ($M)	Change from initial planned cost
NEAR	1996	$259.72	$234.40	-10.80%
Mars Pathfinder	1996	$284.13	$273.20	-4%
Mars Global Surveyor	1996	$211.55	$298.8	29.20%
Lunar Prospector	1998	$62.25	$69.4	10.30%
Mars Climate Orbiter	1998	$336.17	$276.00	-21.80%
Mars Polar Lander	1999	$110.00	$110.00	
Stardust	1999	$205.96	$209.10	1.50%
Genesis	2001	$202.32	$272.30	25.70%
Mars Odyssey	2001	$418.04	$438.20	4.60%
CONTOUR	2002	$153.08	$140.70	-8.80%
Mars Exploration Rovers	2003	$605.00	$809.90	25.30%
MESSENGER	2004	$276.32	$422.50	34.60%
Deep Impact	2005	$268.59	$332.00	19.10%
Mars Reconnaissance Orbiter	2005	$720.00	$720	
New Horizons	2006	$700.00	$700	
Kepler	2007	$474.61	$604.60	21.50%
Dawn	2007	$350.15	$465.00	24.70%
Phoenix	2007	$480.00	$480	
Lunar Reconnaissance Orbiter	2009	$535.49	$590.40	9.30%
Juno	2011	$1,107.00	$1,107.00	0.00%
GRAIL	2011	$495.97	$487.20	-1.80%
Mars Science Laboratory	2011	$1,168.29	$2,523.30	53.70%

Appendix C: Gaussian Landscape Generator

```
function landscape3(dimension,nGaussian,upper,lower,globalvalue,ratio,seed,N)

%---------------------------------------------------------------------------
% This is the initialization and plotting function of the Gaussian landscape
% generator based of the approach from Gallagher and Yuan (2006)
%
% THIS IS A MATLAB *.M FILE
%
% Syntax: landscape3(dimension,nGaussian,upper,lower,globalvalue,ratio, N)
%
% Example: landscape3(2, 100, 5, -5, 1, .8, 1286, 10)
%
% Inputs:
%        dimension = dimensionality
%        nGaussian = number of Gaussian components
%        upper, lower = upper and lower boundaries
%        globalvalue = value of the global optimum
%        ratio = values of local optima ([0,ratio*globalvalue])
%        N = number of sampling points
%
% Outputs (as defined by algorithm from Gallagher and Yuan (2006)):
%        inverse covariance matrix
%        meanvector
%        component peak value
%        3D surface plot
%        2D contour plot
%
%---------------------------------------------------------------------------
% This initialization creates the covariance matrix, mean vector, and
% optimum values.
%---------------------------------------------------------------------------

clear global covmatrix_inv;
clear global meanvector;
clear global optimumvalue;

global covmatrix_inv;   %the inverse covariance matrix of each component
global meanvector;      %the mean of each component
global optimumvalue;    %the peak value of each component

if nargin<6

    disp('Usage:
initialize(dimension,nGaussian,upper,lower,globalvalue,ratio, seed, N)');
    return;

end

if dimension<=1|nGaussian<=0|upper<=lower|globalvalue<=0|ratio<=0|ratio>=1

    disp('Incorrect parameter values!');
```

```
    return;

end

% Generate rotation matrix

e=diag(ones(1,dimension));   % unit diagonal matrix

for i=1:nGaussian

   rotation{i}=e;            % initial rotation matrix for each Gaussian

end

for i=1:nGaussian

  for j=1:dimension-1        % totally n(n-1)/2 rotation matrice

      for k=j+1:dimension

        r=e;
        rand('seed',seed);
        alpha=rand*pi/2-pi/4;% random rotation angle [-pi/4,pi/4]

        r(j,j)=cos(alpha);
        r(j,k)=sin(alpha);
        r(k,j)=-sin(alpha);
        r(k,k)=cos(alpha);

        rotation{i}=rotation{i}*r;

     end

  end

end

% Generate covariance matrix
rand('seed',seed);

% this controls the range of variances
variancerange=(upper-lower)/20;

% add 0.05 to avoid zero variance
variance=rand(nGaussian,dimension)*variancerange+0.05;

for i=1:nGaussian

      covmatrix=diag(variance(i,:));
      covmatrix=rotation{i}'*covmatrix*rotation{i};
      covmatrix_inv{i}=inv(covmatrix);

end
```

```
rand('seed',seed);

% Generate mean vectors randomly within [lower, upper]
meanvector=rand(nGaussian,dimension)*(upper-lower)+lower;

% assign values to components
optimumvalue(1)=globalvalue;     % the first Gaussian is set to be the global
optimum

% values of others are randomly generated within [0,globalvalue*ratio]
optimumvalue(2:nGaussian)=rand(1,nGaussian-1)*globalvalue*ratio;

%--------------------------------------------------------------------------
%This is the fitness function of the Gaussian landscape generator
%
%Syntax: [fitnessvalue,components]=fitness(x)
%
%Inputs:
%        individuals stored in a p-by-n matrix x
%
%Outputs:
%        the fitness value of each row in x
%        the value of each row in x generated by each component
%
%--------------------------------------------------------------------------

global covmatrix_inv;  %the inverse covariance matrix of each component
global meanvector;     %the mean of each component
global optimumvalue;   %the peak value of each component

if isempty(covmatrix_inv)|isempty(meanvector)|isempty(optimumvalue)

    disp('Run initialize function first!');
    return;

end

x = N;

nGaussian=size(meanvector,1);  % total number of components

[p,n]=size(x);                 % p: number of individuals; n: dimensionality

tmp=zeros(nGaussian,p);

%----------------------------------------------------

for i=1:nGaussian

% calculate the values generated by each component

    newx=x-repmat(meanvector(i,:),p,1);

    z=(newx*covmatrix_inv{i}).*newx;
```

```
    tmp(i,:)=sum(z,2)';

end

% f is a nGaussian-by-p matrix
f=exp(-0.5*tmp/n);

% multiply the peak value of each component
f=f.*repmat(optimumvalue',1,p);

% the value of each individual generated by each component
components=f';

% choose the maximum values as the fitness values
fitnessvalue=max(f,[],1);

%--------------------------------------------------------------------------
%This is the plotting function of the Gaussian landscape generator(2D only)
%
%Syntax: plotlandscape(upper,lower,N)
%
%Example:plotlandscape(5,-5,100)
%
%Inputs:
%       upper boundary of the search space
%       lower boundary of the search space
%       number of sampling points
%
%Outputs:
%       3D surface plot
%       2D contour plot
%--------------------------------------------------------------------------

if upper<=lower

    disp('Upper must be larger than Lower!');
    return;

end

if N<10

    disp('Incorrect N value!');
    return;

end

%-----------------------------------------------------

inc=(upper-lower)/N;

x=lower:inc:upper;     %x coordinates
y=lower:inc:upper;     %y coordinates
```

```
d=length(y);

pos=zeros(d*d,2);      %(x,y)coordinates for all sampling points

for i=1:d

    pos((i-1)*d+1:i*d,1)=x(i)*ones(d,1);

end

pos(:,2)=repmat(y',d,1);

f=fitness(pos);        %evaluate individuals

z=vec2mat(f,d)';       %transform into a matrix

figure;

colormap(jet);        %3D surface plot
surfl(x,y,z);
shading interp;

figure;

[C,H]=contour(x,y,z);  %2D contour plot
```

Appendix D: Example From Computational Biology

Fitness landscapes have proven effective in multiple areas of computational biology, such as in mapping out the evolution of drug-resistance in a bacteria or the impact of genetic mechanisms on the adaptability of a biological organism. One example application from Moradigaravand and Engelstädter (2012) uses fitness landscapes (very close in construction to the C^2D model) to map out the role of genetic recombination on the adaptability of an organism. Figure A2.2 highlights the construction of two fitness landscapes used to explore the question about the role of recombination in the presence of genotypes of differing fitness. In the figure, “0” represents a deleterious mutation at a locus, where “1” represents a beneficial mutation for the locus. As a result, the mutational or adaptive pathways to higher fitness (ultimately position “1111” by definition) becomes more complex and indirect.

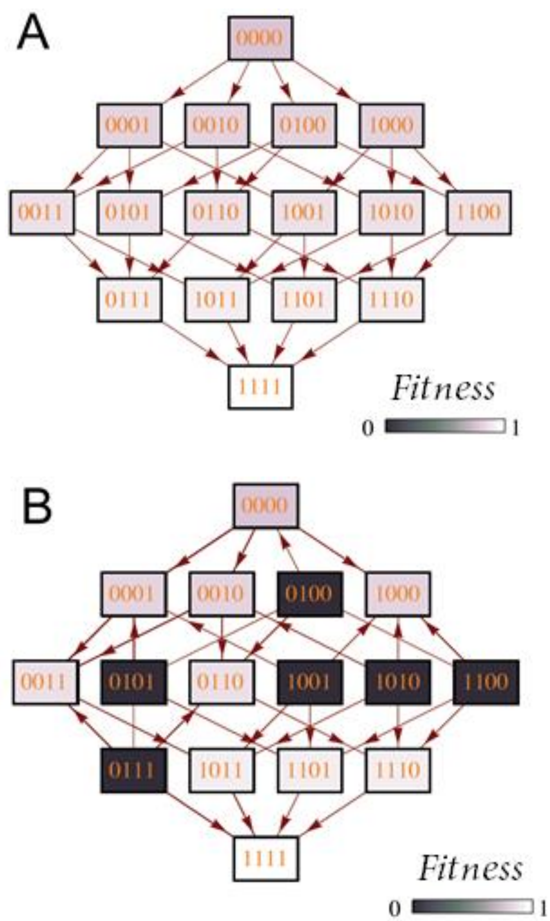


Figure D.1 Fitness Landscape Example from Moradigaravand and Engelstädter (2012). In the figure, the top (A) has no low-fitness genotypes (A) and the bottom has an addition of seven low-fitness genotypes (B)

A key benefit of this fitness landscape approach is the ability to project the evolution and course of a virus or bacteria, specifically as it were to relate to drug-resistance. Safi (2013) uses fitness landscapes for a target protein under selective (i.e. evolutionary) pressure from a single drug or drug cocktail in four drug-target systems: isoniazid-enoyl-ACP reductase (tuberculosis), ritonavir-HIV protease (HIV), methotrexate-dihydrofolate reducatse (breast cancer and leukemia), and gleevec-ABL kinase (leukemia). This vein of research continues to show promise at predicting and describing the evolution of drug resistance in patients. Additionally, it similarly shows potential in its application for designing drugs and organisms to behave in a desired manner. However, these advanced landscapes quickly become amazingly complex. Consider the soil microbiome, where a single gram of soil contains billions of individual cell equivalents (each with their own underlying genetic complexities). Mapping the interactions between these cells and their coevolution with any selective pressure of interest becomes a large metagenomics (study of genetic material recovered directly from environmental samples) and bioinformatics challenge.

APPENDIX E: COBB-DOUGLAS PRODUCTION FIGURE

```
%%%%%%%%%%%%%%%%%%%%%%%
% Graph of Cobb-Douglas Production function and contour curves.
% Generate a meshgrid for variable X_1, e.g. capital, and X_2, e.g. power
%%%%%%%%%%%%%%%%%%%%%%%

[X_1,X_2]=meshgrid(0:.01:1);

% Equation for P=production; in terms of X_1 and X_2

Q=(X_1.^0.50).*X_2.^0.50;

% Plot the surface

surf(X_1,X_2,Q)
hold
Q = 0*X_1 + .8 ;  %desired production is set to 0.8
surf(X_1,X_2,Q)
colormap(bone)
shading interp
view(45,45)

%%%%%%%%%%%%%%%%%
% Generate contours
%%%%%%%%%%%%%%%%%

figure()
colormap(bone)
shading interp
Q=(X_1.^0.50).*X_2.^0.50 ; %return to original equation
[c,h]=contour(X_1,X_2,Q);
clabel(c,h);
```

Appendix F: NK Landscape Calculation for $N = 2$

K=0

Row 1

FR1	FR2	1	2	average	
0	0	0.15	0.11	0.13	Maximally decoupled, *i.e.* each possible binary location only depends on its own state …
0	1	0.15	0.42	0.285	
1	0	0.45	0.11	0.28	
1	1	0.45	0.42	0.435	

Row 2

FR1	FR2	1	2	average	
0	0	0.62	0.54	0.58	…
0	1	0.62	0.37	0.495	
1	0	0.85	0.54	0.695	
1	1	0.85	0.37	0.61	

Row 3

FR1	FR2	1	2	average	
0	0	0.62	0.65	0.635	…. (before averaging, operation repeated over n = k = 10,000)
0	1	0.62	0.61	0.615	
1	0	0.22	0.65	0.435	
1	1	0.22	0.61	0.415	

K=1

Row 1

FR1	FR2	1	2	average	
0	0	0.15	0.11	0.13	Maximally coupled, *i.e.* each possible binary location results in a random fitness value …
0	1	1.00	0.42	0.71	
1	0	0.45	0.54	0.49	
1	1	0.98	0.04	0.51	

Row 2

FR1	FR2	1	2	average	
0	0	0.62	0.54	0.58	…
0	1	0.21	0.37	0.29	
1	0	0.85	0.68	0.77	
1	1	0.95	0.77	0.86	

Row 3

FR1	FR2	1	2	average	
0	0	0.62	0.65	0.63	…. (before averaging, operation repeated over n = k = 10,000)
0	1	0.37	0.61	0.49	
1	0	0.22	0.01	0.11	
1	1	0.59	0.55	0.57	

Appendix G: NK Landscape Calculation for $N = 3$

K=0

Row 1

FR1	FR2	FR3	1	2	3	average	
0	0	0	0.88	0.25	0.44	0.52	Maximally decoupled, *i.e.* each possible binary location only depends on its own state
0	0	1	0.88	0.25	0.98	0.70	
0	1	0	0.88	0.50	0.44	0.61	
0	1	1	0.88	0.50	0.98	0.78	
1	0	0	0.91	0.25	0.44	0.53	
1	0	1	0.91	0.25	0.98	0.71	
1	1	0	0.91	0.50	0.44	0.62	
1	1	1	0.91	0.50	0.98	0.79	

K=1

Row 1

FR1	FR2	FR3	1	2	3	average	
0	0	0	0.83	0.46	0.06	0.45	Partially coupled, *i.e.* depends on *K* neighbors
0	0	1	0.83	0.06	0.58	0.49	
0	1	0	0.46	0.31	0.06	0.28	
0	1	1	0.46	0.11	0.58	0.38	
1	0	0	0.11	0.46	0.83	0.47	
1	0	1	0.11	0.06	0.58	0.25	
1	1	0	0.58	0.31	0.83	0.58	
1	1	1	0.58	0.11	0.58	0.42	

K=2

Row 1

FR1	FR2	FR3	1	2	3	average	
0	0	0	0.92	0.84	0.71	0.82	Maximally coupled, *i.e.* each possible binary location results in a random fitness value
0	0	1	0.89	0.53	0.52	0.68	
0	1	0	0.31	0.51	0.80	0.54	
0	1	1	0.09	0.60	0.57	0.80	
1	0	0	0.75	0.82	0.70	0.39	
1	0	1	0.11	0.15	0.21	0.42	
1	1	0	0.93	0.31	0.58	0.62	
1	1	1	0.10	0.49	0.29	0.83	

Note on Construction for Conceptual Clarification (based on the calculations above):

K \ N=3	
K=0	For the decoupled case, the fitness value depends only on its own state; in the binary case, this means that the cell only depends on whether it is zero or one. To do this we establish a random number to capture the probabilistic fitness value per each possible state per each column; in this case, we randomly generate two numbers for both zero and one, and we do this for each column. We use the normal random function (specifically rand() in Excel for the example generation) to generate six fitness values, i.e. we generate a random fitness value corresponding to each unique state. This is essentially generating a unique fitness value for each zero and one in each of the three columns.
K=1	In the partially coupled example where K is between zero and N minus one, each cell depends on K of N neighbors. Here as K equals one, each location depends on itself as well as one of its neighbors going from left to right and where the rightmost column depends on the leftmost column. To do this we can employ a series of logical checks. We implement this more extensively using arrays; however, for illustration we provide this example using Excel. One logical check as implemented in Excel could include, in the case of binary states: =IF(A12=0, IF(A12=B12, I12,I13), IF(A12=B12,J12,J13)) where columns I and J contain random numbers. This particular logic applies to the first column of the three and first checks if the value is zero. If it is, the command checks if the first column matches it neighboring column to the right. If it does, the model adopts one random value. If the columns do not match, it adopts different random value. However, if the value is one and not zero, the same routine proceeds onto case where the state is one. As a result, each cell in a column in this example takes on one of four possible states (i.e. the number of states raised to K). Similarly, the second column could follow a logical check that compares itself to the column to its right as follows: =IF(B14=0, IF(B14=C14, I15,I17), IF(B14=C14,J15,J17)). Finally, the last column compare itself with the first column as follows: =IF(C14=0, IF(C14=A14, I17,I14), IF(C14=D14,J17,J14)).
K=2	In the case of maximum coupling where K equals N minus one, each cell in the fitness matrix takes on random values because its neighboring states will always vary.

Appendix H: MATLAB Generated C^2D Design Landscape

```
%% insert values for Design Matrix fitness values, N = 3 and K = 1 in example
%% sample values used for Z, we create a row for 0 and for 1
%% we need (2^((K+1)) ) = 2 ^ (3) values  = 8 values => 4 binary locations on x and 2 locations on y
%%  structure plot around required locations
>> Z = [0.410000000000000,0.460000000000000,0.630000000000000,0.380000000000000;0.390000000000000,0.570000000000000,0.550000000000000,0.430000000000000;]

Z =

    0.4100    0.4600    0.6300    0.3800
    0.3900    0.5700    0.5500    0.4300

%% plot
>> bar3(Z)
```

APPENDIX I: UNCOUPLED DESIGN EXAMPLE $(N = 3 \quad K = 0)$

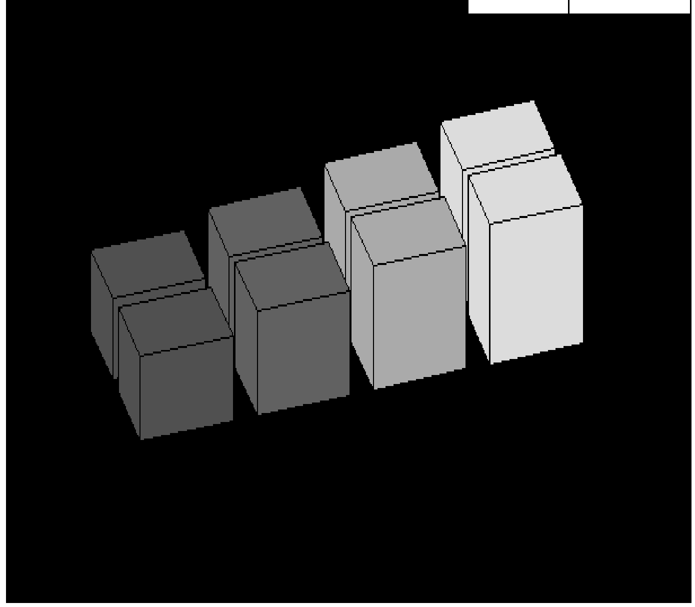
FR_1	FR_2	FR_3

Each design element is fully independent; this design structure adheres to the axioms of design. The design maintains independence between functional requirements and it has the same number of functional requirements as it does design parameters. This represent an uncoupled and ideal design structure.

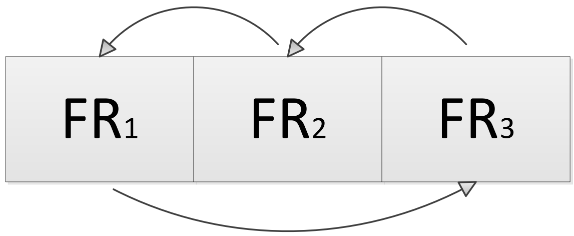
$$\begin{Bmatrix} FR_1 \\ FR_2 \\ FR_3 \end{Bmatrix} = \begin{bmatrix} a_{11} & 0 & 0 \\ 0 & a_{22} & 0 \\ 0 & 0 & a_{33} \end{bmatrix} \begin{Bmatrix} DP_1 \\ DP_2 \\ DP_3 \end{Bmatrix}$$

$$FR_1 = a_{11} DP_1$$
$$FR_2 = a_{22} DP_2$$
$$FR_3 = a_{33} DP_3$$

Location			Fitness Values, j			Avg.
FR1	FR2	FR3	DP1	DP2	DP3	$\frac{1}{n}\sum_{j=n}^{n} j$
0	0	0	0.57	0.05	0.13	0.25
0	0	1	0.57	0.05	0.28	0.30
0	1	0	0.57	0.39	0.13	0.36
0	1	1	0.57	0.39	0.28	0.41
1	0	0	0.61	0.05	0.13	0.26
1	0	1	0.61	0.05	0.28	0.32
1	1	0	0.61	0.39	0.13	0.38
1	1	1	0.61	0.39	0.28	0.43
					F(A)	0.34



APPENDIX J: COUPLED DESIGN EXAMPLE ($N = 3 \quad K = 1$)

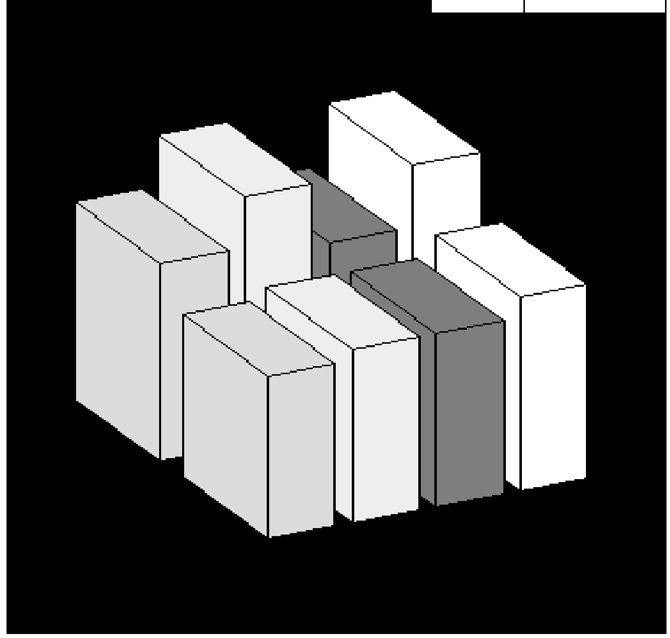


Each design element depends on itself and its neighboring design element. Coupling exists between the functional requirements for this design, resulting in the design no longer having independence between the functional requirements.

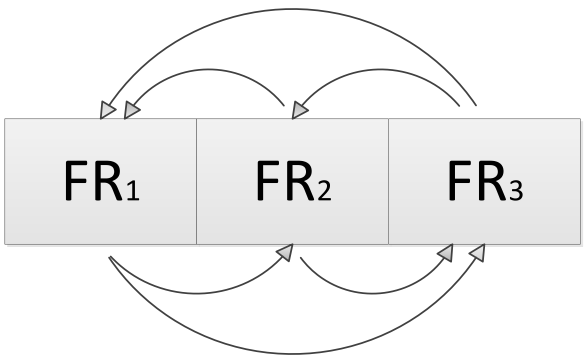
$$\begin{Bmatrix} FR_1 \\ FR_2 \\ FR_3 \end{Bmatrix} = \begin{bmatrix} a_{11} & a_{12} & 0 \\ 0 & a_{22} & a_{23} \\ a_{31} & 0 & a_{33} \end{bmatrix} \begin{Bmatrix} DP_1 \\ DP_2 \\ DP_3 \end{Bmatrix}$$

$$FR_1 = a_{11}DP_1 + a_{12}DP_2$$
$$FR_2 = a_{22}DP_2 + a_{23}DP_3$$
$$FR_3 = a_{31}DP_1 + a_{33}DP_3$$

Location			Fitness Values, j			Avg.
FR1	FR2	FR3	DP1	DP2	DP3	$\frac{1}{n}\sum_{j=n}^{n} j$
0	0	0	0.54	0.45	0.43	0.47
0	0	1	0.54	0.87	0.09	0.50
0	1	0	0.68	0.40	0.43	0.50
0	1	1	0.68	0.90	0.09	0.56
1	0	0	0.67	0.45	0.58	0.57
1	0	1	0.67	0.87	0.63	0.72
1	1	0	0.63	0.40	0.58	0.54
1	1	1	0.63	0.90	0.63	0.72
					F(A)	0.57



Appendix K: Maximally Coupled Example $(N = 3 \quad K = 2)$

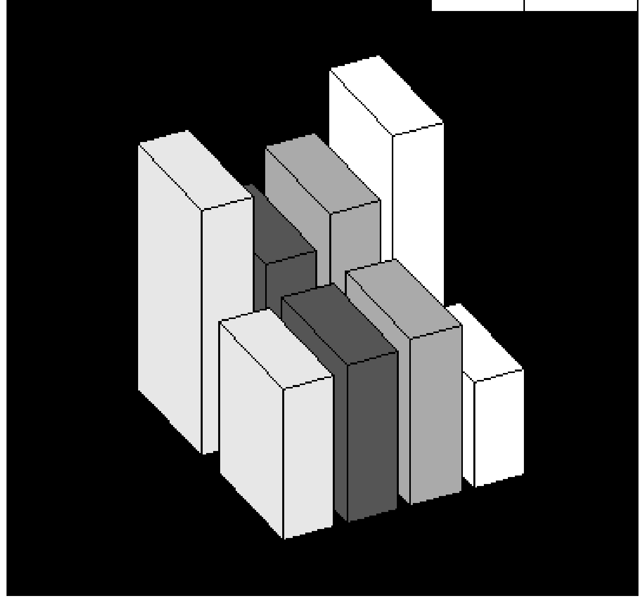


Each design element has maximum interdependence and each design element influences every other design element. This maximally coupled design results in a completely randomized design landscape.

$$\begin{Bmatrix} FR_1 \\ FR_2 \\ FR_3 \end{Bmatrix} = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{Bmatrix} DP_1 \\ DP_2 \\ DP_3 \end{Bmatrix}$$

$$FR_1 = a_{11}DP_1 + a_{12}DP_2 + a_{13}DP_3$$
$$FR_2 = a_{21}DP_1 + a_{22}DP_2 + a_{23}DP_3$$
$$FR_3 = a_{31}DP_1 + a_{32}DP_2 + a_{33}DP_3$$

Location			Fitness Values, j			Avg.
FR1	FR2	FR3	DP1	DP2	DP3	$\frac{1}{n}\sum_{j=n}^{n} j$
0	0	0	0.17	0.93	0.10	0.40
0	0	1	0.80	0.22	0.25	0.42
0	1	0	0.90	0.30	0.10	0.44
0	1	1	0.28	0.25	0.30	0.28
1	0	0	0.87	0.94	0.15	0.65
1	0	1	0.17	0.90	0.30	0.46
1	1	0	0.99	0.07	0.57	0.55
1	1	1	0.75	0.87	0.51	0.71
					F(A)	0.49



Coupled Design Structure

$$\begin{Bmatrix} FR_1 \\ FR_2 \\ FR_3 \end{Bmatrix} = \begin{bmatrix} a_{11} & 0 \\ 0 & a_{22} \\ a_{31} & a_{32} \end{bmatrix} \begin{Bmatrix} DP_1 \\ DP_2 \end{Bmatrix}$$

$$S^* = {}^{1}/_{2} \qquad N = 3 \qquad K = 1$$

When the number of DPs is less than the number of FRs the resulting design matrix is coupled. In these instances, if the coupling elements (i.e. a_{31} or a_{32}) is reduced to zero the design would fail to satisfy all FRs. These designs often mean more complexity than uncoupled or decoupled designs for the same set of FRs.

Decoupled Design

$$\begin{Bmatrix} FR_1 \\ FR_2 \\ FR_3 \end{Bmatrix} = \begin{bmatrix} a_{11} & 0 & 0 \\ a_{21} & a_{22} & 0 \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{Bmatrix} DP_1 \\ DP_2 \\ DP_3 \end{Bmatrix}$$

$$S^* = {}^{1}/_{2} \qquad N = 3 \qquad K = 1$$

In a decoupled design, although the number of DPs equal the number of FRs, there are more design elements a_{ij} than FRs. In this event, if the resulting design can be arranged into a triangular matrix and the design is decoupled. This structure allows for the solution of a design when done in a particular sequence. In this particular design, if the coupling element (i.e. a_{21}) is reduced to zero the design would fail to satisfy all FRs. These designs often can increase imaginary complexity without a strong understanding of the required design sequence by the designer.

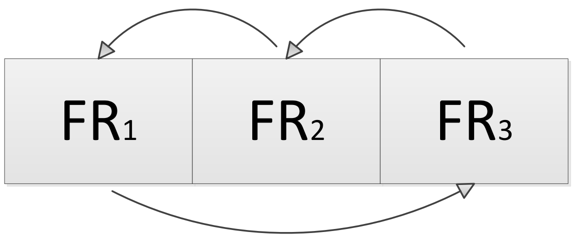
Redundant Design Structure

$$\begin{Bmatrix} FR_1 \\ FR_2 \\ FR_3 \end{Bmatrix} = \begin{bmatrix} a_{11} & a_{12} & 0 & 0 \\ 0 & 0 & a_{23} & 0 \\ 0 & 0 & 0 & a_{34} \end{bmatrix} \begin{Bmatrix} DP_1 \\ DP_2 \\ DP_3 \\ DP_4 \end{Bmatrix}$$

$$S^* = 1 \qquad N = 3 \qquad K = 0$$

In a redundant design, the number of DPs exceed the number of FRs. These designs can also take on various other characteristics, such as coupling, depending on what design parameters vary and which remain fixed. In this particular design, the FRs are independent, and, as a result, the design takes on the characteristics of being an uncoupled design.

Appendix M: Note on Incorporating Design Sensitivities



$$\begin{Bmatrix} FR_1 \\ FR_2 \\ FR_3 \end{Bmatrix} = \begin{bmatrix} a_{11} & a_{12} & 0 \\ 0 & a_{22} & a_{23} \\ a_{31} & 0 & a_{33} \end{bmatrix} \begin{Bmatrix} DP_1 \\ DP_2 \\ DP_3 \end{Bmatrix}$$

Each design element depends on itself and its neighboring design element. Coupling exists between the functional requirements for this design, resulting in the design no longer having the ideal condition of independence between the functional requirements. However, not all interdependencies affect the design performance of other parameters with the same strength. Here we demonstrate how we can incorporate the sensitivities of each design element $a_{ij} = \partial FR_i / \partial DP_j$ if known or calculable. We do so by multiplying each fitness components by the resulting sensitivity.

$$\frac{\partial FR_1}{\partial DP_1} = .8 \quad \frac{\partial FR_1}{\partial DP_2} = .2 \quad \frac{\partial FR_3}{\partial DP_3} = 0$$

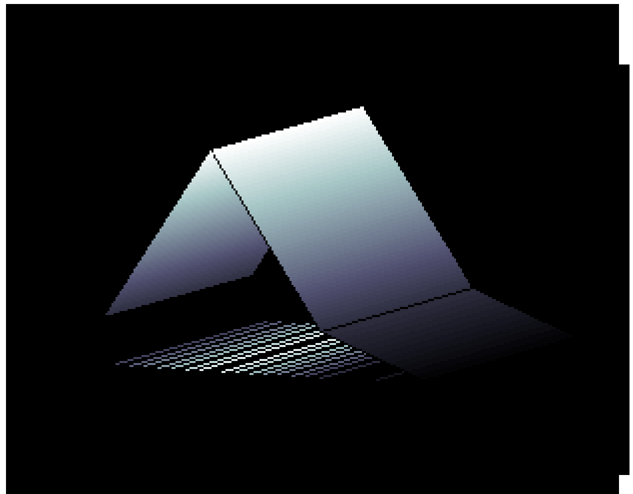
$$\frac{\partial FR_2}{\partial DP_1} = 0 \quad \frac{\partial FR_2}{\partial DP_2} = .7 \quad \frac{\partial FR_2}{\partial DP_3} = .3$$

$$\frac{\partial FR_3}{\partial DP_1} = .4 \quad \frac{\partial FR_3}{\partial DP_2} = 0 \quad \frac{\partial FR_3}{\partial DP_3} = .6$$

For example, if the binary location begins with 1, we multiple the derived NK values by the FR_1 sensitivities $\partial FR_1 / \partial DP_{j=1..f}$, and similarly, if the following location in the binary corresponds to a 1 (i.e. 110 or 111) we repeat this operation by multiplying the binary location by the sensitivities given by $\partial FR_2 / \partial DP_{j=1..f}$. In the event that the binary location remains empty (000), we assign it zero fitness as it has no design parameters to satisfy the functional requirements. Exploration of the space slightly varies, in this specific example, as the average path length to the optima from any location decreases from ~1.3 to 1.25. Although left primarily to future research, the integration of design sensitives to the construction of the design landscape allows the research to incorporate fully the physical relationships of the underlying engineered system.

Appendix N: Designing an Uncoupled Light Switch

Consider two requirements for a dimmer wall switch, which include: 1) to have an on/off control for the light (I/O), and, 2) the ability to control the intensity of the light (L). In this design, the number of DPs equals the number of FRs and the resulting design matrix is uncoupled. In this design, the sliding switch up and down (Y) controls light intensity and the switch left and right (X) controls the light being on or off.



Generic $K = 0$ additive landscape

$$\begin{Bmatrix} L \\ I/O \end{Bmatrix} = \begin{bmatrix} a_{11} & 0 \\ 0 & a_{22} \end{bmatrix} \begin{Bmatrix} Y \\ X \end{Bmatrix}$$

$$L = a_{11}Y \quad I/O = a_{21}X$$

$$S^* = 1 \quad N = 2 \quad K = 0$$

APPENDIX O: BETTER? ALGORITHM $(f_{ADMUs_{0105}})$

```
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
;; V3.5.4.2 – Version allows for the better? calculation - even if not using hill climbing
;; This calculation allows us to report when an ADMU has achieved an improved fitness score
;;
;; If using hill climbing V3.5.4.1, better? is operational (two versions are not compatible for results
;; without normalization, as the new calculations add to the time for the model to run).
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
to go
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
;; if not hill_climbing? and needed better, the following code is used
ask turtles [ if ticks mod 2 = 0 [ set last_fitness1? fitness ] ]       ;; fitness if mod 2 of ticks = 1
(even tick)
ask turtles [ if ticks mod 2 = 1 [ set last_fitness2? fitness ] ]       ;; if mod 2 of ticks = 0  (odd tick)
ask turtles
  [
      if ticks mod 2 = 0 and last_fitness2? < fitness [ set better? true ]
;; if it is an even tick then odd was last
     if ticks mod 2 = 1 and last_fitness1? < fitness [ set better? true ]
;; if it is an odd tick then even was last
     if ticks mod 2 = 0 and last_fitness2? >= fitness [ set better? false ]
     if ticks mod 2 = 1 and last_fitness1? >= fitness [ set better? false ]  ]
….
end

;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
;; Note v3.5.4.1 uses the following command (only works with hill climbing):
;; let old-patch patch-here
;; climb
;; if old-patch < patch-here [set better? true]
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
```

APPENDIX P: *PICK-TEAM MEMBERS ALGORITHM* $(F_{COL_{01}})$

```
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
;; Choose turtles to be in a new team (based off of and adopted from Bakshy and Wilensky 2007)
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
to pick-team-members
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;

  let new-team-member nobody ;;;; an individual agent outside of set, nobody
  set newcomers_team_cnt 0
  repeat team-size
  [
    ;; With a probability p have a newcomer join the team

  ifelse random-float 100.0 <= prob_of_newcomer
    [
      make-newcomer
      set new-team-member newcomer
      set newcomers_team_cnt newcomers_team_cnt + 1
    ]

    [
;; With a probability q, choose a new team member who was a previous collaborator of an existing team member, given team has at least one previous collaborator; otherwise agent will collaborate with a previous incumbent.

ifelse random-float 100.0 <= propensity_to_repeat_collaboration and any? (turtles with [in-team? and (any? link-neighbors with [not in-team?])])

 [set new-team-member one-of turtles with [not in-team? and (any? link-neighbors with [in-team?])]]
 [set new-team-member one-of turtles with [not in-team?]]
    ]

    if count turtles with [not in-team?] > 0
    [
      ask new-team-member  ;; specifies turtle to become a new team member
      [
        set in-team? true
        set downtime 0
        set size 4.8
        set color ifelse-value incumbent? [yellow + 2] [blue + 1]
      ]
    ]
  ]
end
```

Appendix Q: Hypothesis 1 For Team-Size

Table Q.1 H1: Test of Between-Subjects Effects for Team-Size without Consensus

Source	Dep. Var.	Type III Sum of Squares	df	Mean Square	F	Sig.	η^2	Noncent. Param.	Obs. Power[d]
Corr. Model	f_t	368.715[a]	19	19.406	.959	.509	.009	18.213	.730
	$\overline{f_t}$	7018.742[b]	19	369.407	22.435	.000	.177	426.264	1.000
	t_s	35935.992[c]	19	1891.368	3.721	.000	.034	70.692	1.000
Inter.	f_t	12593515.950	1	12593515.950	622056.574	.000	.997	622056.574	1.000
	$\overline{f_t}$	8879428.505	1	8879428.505	539268.305	.000	.996	539268.305	1.000
	t_s	2236734.728	1	2236734.728	4400.023	.000	.690	4400.023	1.000
Team-size (n)	f_t	368.715	19	19.406	.959	.509	.009	18.213	.730
	$\overline{f_t}$	7018.742	19	369.407	22.435	.000	.177	426.264	1.000
	t_s	35935.992	19	1891.368	3.721	.000	.034	70.692	1.000
Error	f_t	40085.038	1980	20.245					
	$\overline{f_t}$	32602.080	1980	16.466					
	t_s	1006525.280	1980	508.346					
Total	f_t	12633969.703	2000						
	$\overline{f_t}$	8919049.327	2000						
	t_s	3279196.000	2000						
Corr. Total	f_t	40453.753	1999						
	$\overline{f_t}$	39620.822	1999						
	t_s	1042461.272	1999						

a. R Squared = .009 (Adjusted R Squared = .000)

b. R Squared = .117 (Adjusted R Squared = .169)

c. R Squared = .034 (Adjusted R Squared = .025)

d. Computed using alpha = .05

Table Q.2 H1: Test of Between-Subjects Effects for Team-Size with Consensus Required

Source	Dep. Var.	Type III Sum of Squares	df	Mean Square	F	Sig.	η^2	Noncent. Param.	Obs. Power[d]
Corr. Model	t_s	6352936.937[a]	13	488687.457	8.410	.000	.038	109.329	1.000
	f_t	192.016[b]	13	14.770	.337	.986	.002	4.385	.207
	$\overline{f_t}$	8061.537[c]	13	620.118	15.980	.000	.069	207.739	1.000
Inter.	t_s	218497513.423	1	218497513.423	3760.168	.000	.574	3760.168	1.000
	f_t	19544600.887	1	19544600.887	446322.848	.000	.994	446322.848	1.000
	$\overline{f_t}$	16026078.753	1	16026078.753	412978.734	.000	.993	412978.734	1.000
Team-size (n)	t_s	6352936.937	13	488687.457	8.410	.000	.038	109.329	1.000
	f_t	192.016	13	14.770	.337	.986	.002	4.385	.207
	$\overline{f_t}$	8061.537	13	620.118	15.980	.000	.069	207.739	1.000
Error	t_s	161890145.640	2786	58108.451					
	f_t	121999.710	2786	43.790					
	$\overline{f_t}$	108113.691	2786	38.806					
Total	t_s	386740596.000	2800						
	f_t	19666792.613	2800						
	$\overline{f_t}$	16142253.981	2800						
Corr. Total	t_s	168243082.577	2799						
	f_t	122191.726	2799						
	$\overline{f_t}$	116175.228	2799						

a. R Squared = .038 (Adjusted R Squared = .033)

b. R Squared = .002 (Adjusted R Squared = -.003)

c. R Squared = .069 (Adjusted R Squared = .065)

d. Computed using alpha = .05

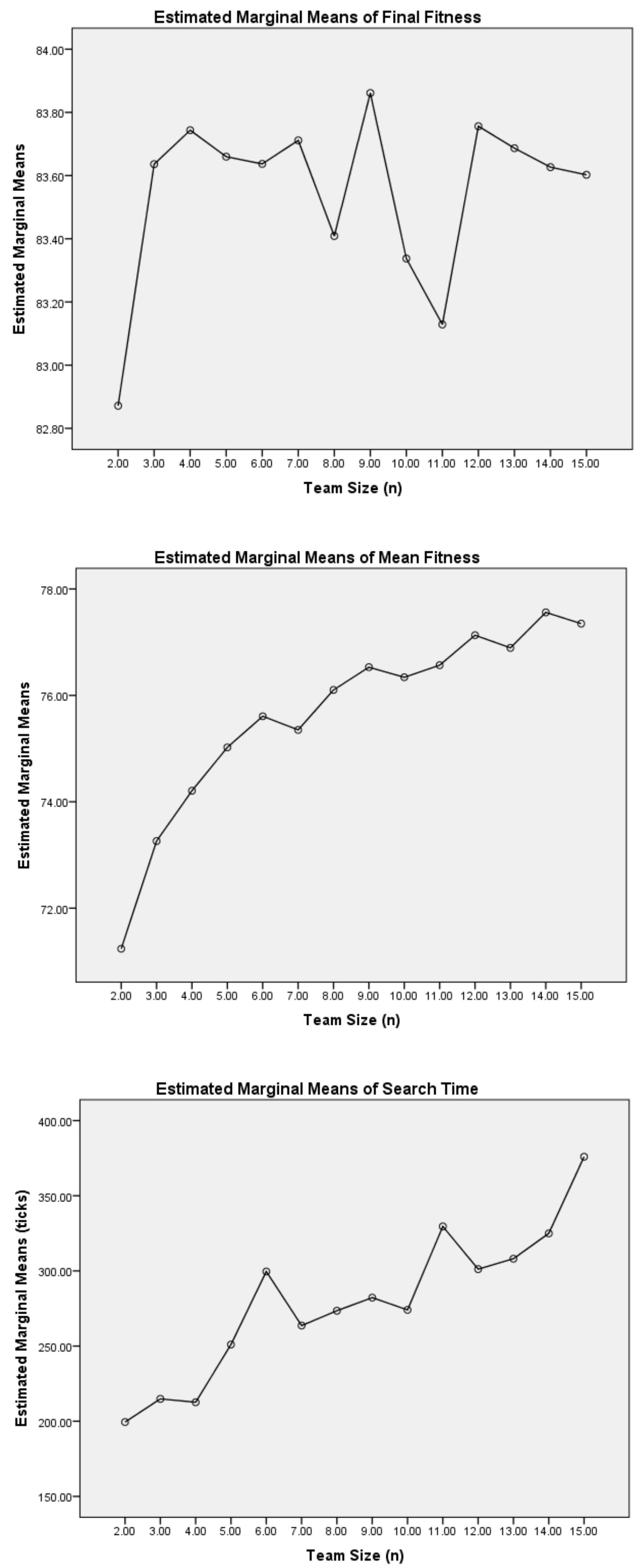


Figure Q.1 H1: Estimated Marginal Means with Consensus Required

Table Q.3 H1: Test of Between-Subjects Effects for Team-Size Parity (n = 1 … 15)

Ranks

		N	Mean Rank	Sum of Ranks
even_mean_fitness-odd_mean_fitness	Negative Ranks	784[a]	719.09	563764.00
	Positive Ranks	616[b]	676.84	416936.00
	Ties	0[c]		
	Total	1400		
even_total_ticks-odd_total_ticks	Negative Ranks	694[d]	670.70	465465.00
	Positive Ranks	608[e]	629.59	382788.00
	Ties	98[f]		
	Total	1400		

a. even_mean_fitness < odd_mean_fitness

b. even_mean_fitness > odd_mean_fitness

c. even_mean_fitness = odd_mean_fitness

d. even_total_ticks < odd_total_ticks

e. even_total_ticks > odd_total_ticks

f. even_total_ticks = odd_total_ticks

Descriptive Statistics

	N	Min	Max	Mean	Std. Deviation
odd_final_fitness	1400	62.01	100.00	83.6124	6.56777
odd_mean_fitness	1400	58.57	99.75	75.8537	6.37751
odd_total_ticks	1400	6.00	1000.00	289.3429	251.77735
even_final_fitness	1400	54.51	100.00	83.4830	6.64818
even_mean_fitness	1400	55.74	99.57	75.4552	6.50304
even_total_ticks	1400	6.00	1000.00	269.3514	238.04984
Valid N (listwise)	1400				

Test Statistics[a]

	even_mean_fitness - odd_mean_fitness	even_total_ticks - odd_total_ticks
Z	-4.463	-2.356
Asymp. Sig. (2-tailed)	.000	.018

a. Sign Test

Table Q.4 H1: Test of Between-Subjects Effects for Team-Size Parity (n= 5…9)

Ranks

		N	Mean Rank	Sum of Ranks
even_mean_fitness - odd_mean_fitness	Negative Ranks	152 [a]	191.08	29044.00
	Positive Ranks	248 [b]	206.27	51156.00
	Ties	0 [c]		
	Total	400		
even_total_ticks - odd_total_ticks	Negative Ranks	152 [d]	200.76	30516.00
	Positive Ranks	226 [e]	181.92	41115.00
	Ties	22 [f]		
	Total	400		

a. even_mean_fitness < odd_mean_fitness

b. even_mean_fitness > odd_mean_fitness

c. even_mean_fitness = odd_mean_fitness

d. even_total_ticks < odd_total_ticks

e. even_total_ticks > odd_total_ticks

f. even_total_ticks = odd_total_ticks

Descriptive Statistics

	N	Min	Max	Mean	Std. Deviation
odd_final_fitness	600	69.46	100.00	83.7442	6.42599
odd_mean_fitness	600	58.57	99.67	75.6349	6.18704
odd_total_ticks	600	6.00	1000.00	265.6300	228.96838
even_final_fitness	400	68.24	100.00	83.5229	6.41471
even_mean_fitness	400	62.19	99.09	75.8550	6.04824
even_total_ticks	400	6.00	1000.00	286.5650	246.00806
Valid N (listwise)	400				

Test Statistics[a]

	even_mean_fitness - odd_mean_fitness	even_total_ticks - odd_total_ticks
Z	-4.778 [b]	-2.493 [b]
Asymp. Sig. (2-tailed)	.000	.013

a. Wilcoxon Signed Ranks Tests

b. Based on negative ranks.

Table Q.5 H1: Correlations Using Composite Data Set and Consensus Required [b c]

		f_t	$\overline{f_t}$	t_s
	Spearman's Rho Correlation Coefficient	.015	.418**	.190**
n [a]	Sig. (2-tailed)	.101	0.000	.000
	N	11397	11397	11397
	Pearson Correlation	.026**	.411**	.173**
n [a]	Sig. (2-tailed)	.005	.000	.000
	N	11397	11397	11397

a. Data based on overall composite test of all variables from Hypothesis 1
b. Strategies Enabled (Continuous Diversity and Situational Management Strategies)
c. n = (2,3, 6, 7, 10, 11), m = (10, 20, 50), p = (20, 50, 80), q = (20, 50, 80), mdt = [10 5 60], S = 10

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

Table Q.6 H1: Correlations Using Composite Data Set with Consensus Required

Tests of Between-Subjects Effects

Source	Dep. Var	Type III Sum of Squares	df	Mean Square	F	Sig.	Noncent. Parameter	Obs. Power[d]
Corrected Model	f_t	43040.990[a]	1628	26.438	1.054	.079	1716.033	1.000
	t_s	149456968.747[b]	1628	91804.035	1.258	.000	2047.405	1.000
	$\overline{f_t}$	72078.057[c]	1628	44.274	3.060	.000	4981.140	1.000
Intercept	f_t	56290714.880	1	56290714.880	2244296.409	.000	2244296.41	1.000
	t_s	1239342731.653	1	1239342731.653	16977.703	.000	16977.703	1.000
	$\overline{f_t}$	45019431.192	1	45019431.192	3111183.792	.000	3111183.79	1.000
m	f_t	64.207	2	32.103	1.280	.278	2.560	.279
	t_s	173025.304	2	86512.652	1.185	.306	2.370	.261
	$\overline{f_t}$	15.661	2	7.830	.541	.582	1.082	.140
n	f_t	97.345	5	19.469	.776	.567	3.881	.283
	t_s	21843925.949	5	4368785.190	59.848	.000	299.239	1.000
	$\overline{f_t}$	33412.359	5	6682.472	461.809	.000	2309.047	1.000
p	f_t	146.269	2	73.135	2.916	.054	5.832	.571
	t_s	6437354.052	2	3218677.026	44.093	.000	88.185	1.000
	$\overline{f_t}$	7507.725	2	3753.863	259.420	.000	518.841	1.000

Table Q.6 H1: Correlations Using Composite Data Set and Consensus Required (Continued)

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Noncent. Parameter	Obs. Power[d]
q	f_t	20.600	2	10.300	.411	.663	.821	.117
	t_s	429452.515	2	214726.258	2.942	.053	5.883	.575
	$\overline{f_t}$	23.902	2	11.951	.826	.438	1.652	.192
mdt	f_t	170.682	10	17.068	.681	.744	6.805	.368
	t_s	859555.485	10	85955.548	1.178	.301	11.775	.629
	$\overline{f_t}$	1116.749	10	111.675	7.718	.000	77.176	1.000
m * n	f_t	162.109	9	18.012	.718	.693	6.463	.365
	t_s	899406.523	9	99934.058	1.369	.196	12.321	.675
	$\overline{f_t}$	39.476	9	4.386	.303	.974	2.728	.159
m * p	f_t	53.352	4	13.338	.532	.712	2.127	.180
	t_s	528836.552	4	132209.138	1.811	.124	7.245	.556
	$\overline{f_t}$	17.643	4	4.411	.305	.875	1.219	.119
m * q	f_t	133.139	4	33.285	1.327	.257	5.308	.419
	t_s	343257.817	4	85814.454	1.176	.319	4.702	.373
	$\overline{f_t}$	36.192	4	9.048	.625	.644	2.501	.207
m * mdt	f_t	519.939	20	25.997	1.036	.413	20.730	.793
	t_s	1176044.037	20	58802.202	.806	.710	16.111	.651
	$\overline{f_t}$	228.584	20	11.429	.790	.729	15.797	.640
n * p	f_t	148.427	10	14.843	.592	.822	5.918	.318
	t_s	2393542.204	10	239354.220	3.279	.000	32.789	.991
	$\overline{f_t}$	392.763	10	39.276	2.714	.002	27.143	.970
n * q	f_t	358.187	10	35.819	1.428	.161	14.281	.734
	t_s	878063.941	10	87806.394	1.203	.283	12.029	.640
	$\overline{f_t}$	94.235	10	9.423	.651	.770	6.512	.351
n * mdt	f_t	1132.974	50	22.659	.903	.667	45.171	.961
	t_s	4039770.695	50	80795.414	1.107	.281	55.341	.990
	$\overline{f_t}$	651.436	50	13.029	.900	.673	45.019	.960
p * q	f_t	65.237	4	16.309	.650	.627	2.601	.214
	t_s	54320.910	4	13580.228	.186	.946	.744	.090
	$\overline{f_t}$	41.863	4	10.466	.723	.576	2.893	.236
p * mdt	f_t	471.727	20	23.586	.940	.534	18.808	.740
	t_s	1214613.023	20	60730.651	.832	.676	16.639	.670
	$\overline{f_t}$	732.969	20	36.648	2.533	.000	50.654	.999

Table Q.6 Correlations Using Composite Data Set and Consensus Required (Continued)

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Noncent. Parm.	Obs. Power[d]
q * mdt	f_t	510.555	20	25.528	1.018	.436	20.356	.784
	t_s	1128765.027	20	56438.251	.773	.749	15.463	.628
	$\overline{f_t}$	335.611	20	16.781	1.160	.280	23.193	.849
m * n * p	f_t	391.333	17	23.020	.918	.552	15.602	.670
	t_s	585289.550	17	34428.797	.472	.966	8.018	.341
	$\overline{f_t}$	244.540	17	14.385	.994	.461	16.900	.716
m * n * q	f_t	588.625	18	32.701	1.304	.174	23.468	.872
	t_s	1786453.817	18	99247.434	1.360	.140	24.473	.889
	$\overline{f_t}$	317.873	18	17.660	1.220	.234	21.967	.842
m * n * mdt	f_t	2096.127	90	23.290	.929	.670	83.572	.998
	t_s	6689705.384	90	74330.060	1.018	.432	91.642	.999
	$\overline{f_t}$	1286.163	90	14.291	.988	.514	88.884	.999
m * p * q	f_t	186.397	8	23.300	.929	.491	7.432	.443
	t_s	195390.868	8	24423.858	.335	.953	2.677	.165
	$\overline{f_t}$	96.507	8	12.063	.834	.573	6.669	.397
m * p * mdt	f_t	1090.553	40	27.264	1.087	.326	43.480	.970
	t_s	3141679.446	40	78541.986	1.076	.343	43.038	.968
	$\overline{f_t}$	440.710	40	11.018	.761	.862	30.456	.851
m * q * mdt	f_t	1028.507	40	25.713	1.025	.426	41.006	.958
	t_s	3031522.387	40	75788.060	1.038	.404	41.529	.961
	$\overline{f_t}$	509.293	40	12.732	.880	.686	35.196	.913
n * p * q	f_t	517.642	20	25.882	1.032	.419	20.638	.791
	t_s	1790946.116	20	89547.306	1.227	.220	24.534	.874
	$\overline{f_t}$	294.286	20	14.714	1.017	.437	20.337	.783
n * p * mdt	f_t	2112.882	100	21.129	.842	.870	84.240	.998
	t_s	7163786.475	100	71637.865	.981	.534	98.136	1.000
	$\overline{f_t}$	1344.453	100	13.445	.929	.679	92.912	.999
n * q * mdt	f_t	2717.292	100	27.173	1.083	.269	108.338	1.000
	t_s	6991037.683	100	69910.377	.958	.601	95.770	1.000
	$\overline{f_t}$	1395.424	100	13.954	.964	.582	96.434	1.000
p * q * mdt	f_t	1215.747	40	30.394	1.212	.169	48.472	.985
	t_s	3035046.864	40	75876.172	1.039	.402	41.577	.961
	$\overline{f_t}$	625.334	40	15.633	1.080	.336	43.215	.969
m * n * p * q	f_t	695.621	33	21.079	.840	.727	27.734	.842
	t_s	3063776.001	33	92841.697	1.272	.137	41.971	.976
	$\overline{f_t}$	413.608	33	12.534	.866	.687	28.583	.857

Table Q.6 Correlations Using Composite Data Set and Consensus Required (Continued)

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Noncent. Param.	Obs. Power[d]
m * n * p * mdt	f_t	4768.377	170	28.049	1.118	.141	190.114	1.000
	t_s	11178896.442	170	65758.214	.901	.817	153.139	1.000
	$\overline{f_t}$	2326.529	170	13.685	.946	.681	160.781	1.000
m * n * q * mdt	f_t	4887.192	180	27.151	1.083	.215	194.851	1.000
	t_s	11294965.024	180	62749.806	.860	.912	154.729	1.000
	$\overline{f_t}$	2338.905	180	12.994	.898	.831	161.636	1.000
m * p * q * mdt	f_t	1757.179	80	21.965	.876	.778	70.058	.994
	t_s	5003585.395	80	62544.817	.857	.815	68.544	.993
	$\overline{f_t}$	1208.806	80	15.110	1.044	.372	83.538	.999
n * p * q * mdt	f_t	6033.506	200	30.168	1.203	.028	240.554	1.000
	t_s	14997483.465	200	74987.417	1.027	.382	205.450	1.000
	$\overline{f_t}$	2692.966	200	13.465	.931	.749	186.104	1.000
m * n * p * q * mdt	f_t	8310.305	320	25.970	1.035	.323	331.330	1.000
	t_s	24154526.803	320	75482.896	1.034	.329	330.892	1.000
	$\overline{f_t}$	4899.870	320	15.312	1.058	.231	338.618	1.000
Error	f_t	244997.809	9768	25.082				
	t_s	713046997.58	9768	72998.259				
	$\overline{f_t}$	141344.849	9768	14.470				
Total	f_t	74992986.461	11397					
	t_s	2481233959.0	11397					
	$\overline{f_t}$	59698641.891	11397					
Corrected Total	f_t	288038.799	11396					
	t_s	862503966.33	11396					
	$\overline{f_t}$	213422.906	11396					

a. R Squared = .149 (Adjusted R Squared = .008)

b. R Squared = .173 (Adjusted R Squared = .035)

c. R Squared = .338 (Adjusted R Squared = .227)

d. Computed using alpha = .05

e. Smoothness = 10; m = 10, 20, 50; p = 20, 50, 80; q = 20, 50, 80; mdt = [10 5 60] ; n = 2,3, 6, 7, 10, 11

Table Q.7 H1: Verifying Correlations with New Simulation and No Consensus Required [b c]

		f_t	$\overline{f_t}$	t_s
	Spearman's Rho Correlation Coefficient	-.065**	.352**	.264**
n	Sig. (2-tailed)	.003	.000	.000
	N	2000	2000	2000
	Pearson Correlation	-.084**	.367**	.152**
n	Sig. (2-tailed)	.000	.000	.000
	N	2000	2000	2000

a. Data generated from new simulation to test and confirm that correlations strengthen with less smoothness on the design landscape. More complex relationship uncovered as seen below.
b. Strategies Disabled (Continuous Diversity and Situational Management Strategies)
c. n = [2 1 21], m = 50, p = 50, q = 85, mdt = 40, S = 30
**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

Table Q.8 H1: Verifying Correlations with New Simulation and No Consensus Required [b c]

		f_t	$\overline{f_t}$	t_s
	Spearman's Rho Correlation Coefficient	.104**	.432**	.359**
n	Sig. (2-tailed)	.000	.000	.000
	N	1400	1400	1400
	Pearson Correlation	.125**	.463**	.312**
n	Sig. (2-tailed)	.000	.000	.000
	N	1400	1400	1400

a. Strategies Disabled (Continuous Diversity and Situational Management Strategies)
b. n = [2 1 15], m = 10, p = 50, q = 85, mdt = 40, S = 50
**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

Table Q.9 H1: Verifying Correlations with New Simulation and No Consensus Required [b c]

		f_t	$\overline{f_t}$	t_s
	Spearman's Rho Correlation Coefficient	-.086**	.109**	.346**
n	Sig. (2-tailed)	.000	.000	.000
	N	1400	1400	1400
	Pearson Correlation	.121**	.156**	.348**
n	Sig. (2-tailed)	.000	.000	.000
	N	1400	1400	1400

a. Strategies Disabled (Continuous Diversity and Situational Management Strategies)
b. n = [2 1 15], m = 10, p = 50, q = 85, mdt = 40, S = 100
**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

Appendix R: Hypothesis 1 Probability of a Newcomer

Table R.1 H1: Test of Between-Subject Effects for Probability of Incorporating a Newcomer Test

Source	Dep. Var.	Type III Sum of Squares	df	Mean Square	F	Sig.	η^2	Noncent. Param.	Obs. Power[d]
Corr. Model	f_t	4951.319[a]	25	198.053	5.596	.000	.052	139.898	1.00
	$\overline{f_t}$	7971.777[b]	25	318.871	12.691	.000	.110	317.263	1.00
	t_s	15914204.54[c]	25	636568.182	10.257	.000	.091	256.428	1.00
Inter.	f_t	17614032.063	1	17614032.063	497679.12	.000	.995	497679.1	1.000
	$\overline{f_t}$	14046560.725	1	14046560.725	559028.55	.000	.995	559028.5	1.000
	t_s	260161812.57	1	260161812.57	4192.026	.000	.620	4192.026	1.000
p	f_t	164.125	12	13.677	.386	.969	.002	4.637	.227
	$\overline{f_t}$	2078.660	12	173.222	6.894	.000	.031	82.727	1.000
	t_s	1530474.422	12	127539.535	2.055	.017	.009	24.661	.937
S (.5, .1)	f_t	4546.329	1	4546.329	128.455	.000	.048	128.455	1.000
	$\overline{f_t}$	5732.376	1	5732.376	228.139	.000	.081	228.139	1.000
	t_s	14100587.225	1	14100587.225	227.205	.000	.081	227.205	1.000
$p * S$	f_t	240.865	12	20.072	.567	.870	.003	6.806	.337
	$\overline{f_t}$	160.741	12	13.395	.533	.894	.002	6.397	.316
	t_s	283142.895	12	23595.241	.380	.971	.002	4.562	.224
Error	f_t	91099.901	2574	35.392					
	$\overline{f_t}$	64676.208	2574	25.127					
	t_s	159745326.88	2574	62061.122					
Total	f_t	17710083.283	2600						
	$\overline{f_t}$	14119208.710	2600						
	t_s	435821344.00	2600						
Corr. Total	f_t	96051.220	2599						
	$\overline{f_t}$	72647.985	2599						
	t_s	175659531.42	2599						

a. R Squared = .052 (Adjusted R Squared = .042)

b. R Squared = .110 (Adjusted R Squared = .101)

c. R Squared = .091 (Adjusted R Squared = .082)

d. Computed using alpha = .05

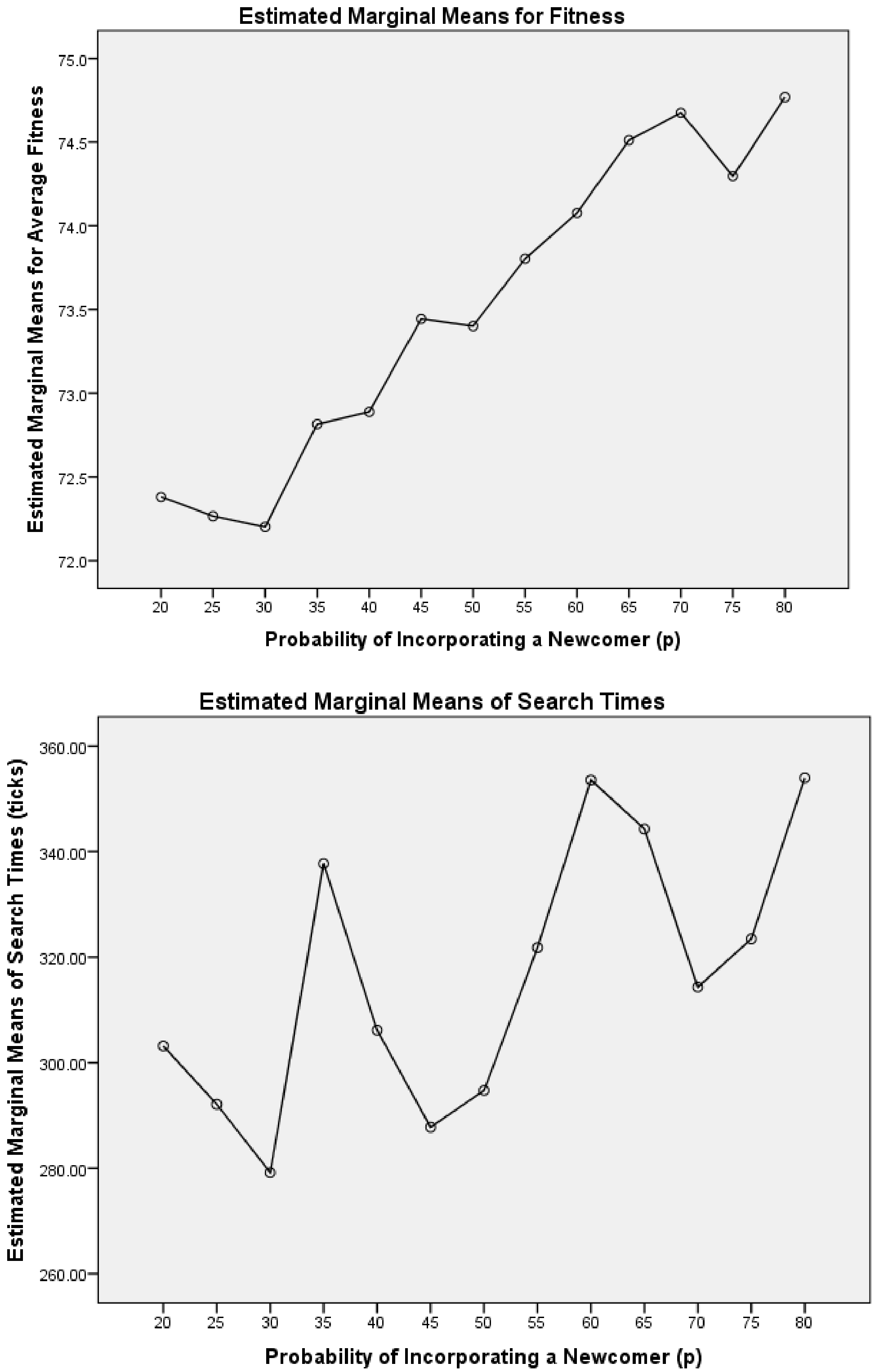


Figure R.1 H1: Estimated Marginal Means for Probability of Newcomers to Performance

Table R.2 H1: Correlations Using Composite Data Set and Consensus Required [b c]

		f_t	$\overline{f_t}$	t_s
	Spearman's Rho Correlation Coefficient	.012	.196**	.096**
p [a]	Sig. (2-tailed)	.190	.000	.000
	N	11397	11397	11397
	Pearson Correlation	.020*	.189**	.078**
p [a]	Sig. (2-tailed)	.030	.000	.000
	N	11397	11397	11397
		f_t	$\overline{f_t}$	t_s
	Spearman's Rho Correlation Coefficient	-.019*	-.066**	-.043**
m [a]	Sig. (2-tailed)	.038	.000	.000
	N	11397	11397	11397
	Pearson Correlation	-.018	-.078**	-.047**
m [a]	Sig. (2-tailed)	.060	.000	.000
	N	11397	11397	11397

a. Data based on overall composite test of all variables from Hypothesis 1
b. Strategies Enabled (Continuous Diversity and Situational Management Strategies)
c. n = (2,3, 6, 7, 10, 11), m = (10, 20, 50), p = (20, 50, 80), q = (20, 50, 80), mdt = [10 5 60], S = 10
**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

APPENDIX S: HYPOTHESIS 1 PROPENSITY TO REPEAT

Table S.1 H1: Test of Between-Subject Effects for Propensity of Repeating a Collaboration

Source	Dep. Var.	Type III Sum of Squares	df	Mean Square	F	Sig.	η^2	Noncent. Param.	Obs. Power[d]
Corr. Model	f_t	988.311[a]	30	32.944	1.319	.122	.072	39.573	.965
	$\overline{f_t}$	3500.545[b]	30	116.685	7.072	.000	.294	212.153	1.000
	t_s	3519603.240[c]	30	117320.108	2.715	.000	.138	81.444	1.000
Inter.	f_t	2263862.520	1	2263862.520	90646.464	.000	.994	90646.464	1.000
	$\overline{f_t}$	1736837.816	1	1736837.816	105262.13	.000	.995	105262.136	1.000
	t_s	8784582.547	1	8784582.547	203.276	.000	.285	203.276	1.000
q	f_t	988.311	30	32.944	1.319	.122	.072	39.573	.965
	$\overline{f_t}$	3500.545	30	116.685	7.072	.000	.294	212.153	1.000
	t_s	3519603.240	30	117320.108	2.715	.000	.138	81.444	1.000
Error	f_t	12712.090	509	24.975					
	$\overline{f_t}$	8398.561	509	16.500					
	t_s	21996483.313	509	43215.095					
Total	f_t	3690309.184	540						
	$\overline{f_t}$	2928529.797	540						
	t_s	50572707.000	540						
Corr. Total	f_t	13700.402	539						
	$\overline{f_t}$	11899.106	539						
	t_s	25516086.554	539						

a. R Squared = .072 (Adjusted R Squared = .017)
b. R Squared = .294 (Adjusted R Squared = .253)
c. R Squared = .138 (Adjusted R Squared = .087)
d. Computed using alpha = .05

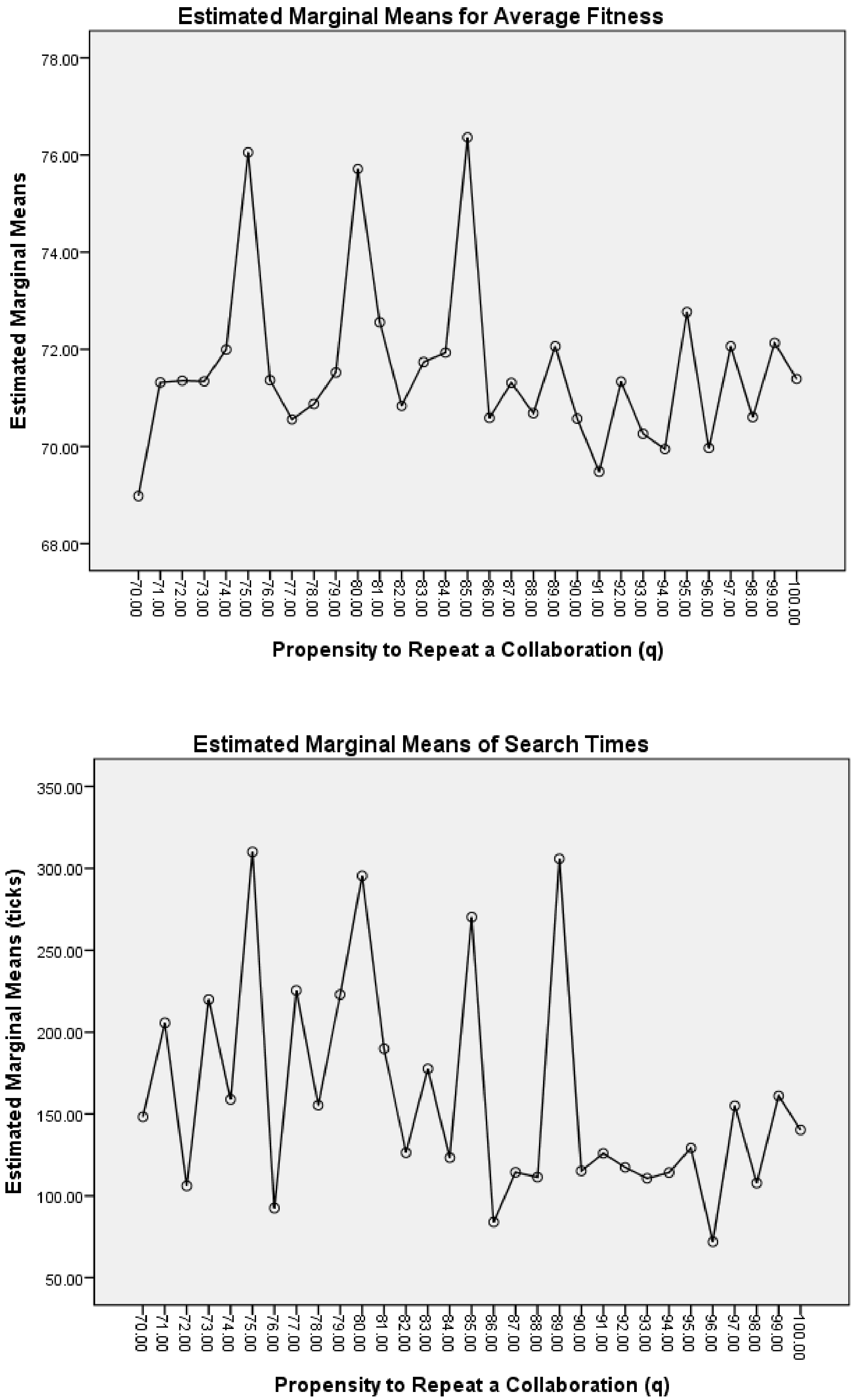


Figure S.1 H1: Estimated Marginal Means for Repeating Collaboration to Performance

Table S.2 H1: Test of Between-Subject Effects for Propensity of Repeating a Collaboration

Source	Dep. Var.	Type III Sum of Squares	df	Mean Square	F	Sig.	η^2	Noncent. Param.	Obs. Power[c]
Corr. Model	c_t	.080[a]	30	.003	2.434	.000	.144	73.030	1.000
	$\overline{c_t}$	.048[b]	30	.002	3.096	.000	.176	92.873	1.000
Inter.	c_t	302.421	1	302.421	274543.83	.000	.998	274543.835	1.000
	$\overline{c_t}$	305.800	1	305.800	595694.26	.000	.999	595694.264	1.000
q	c_t	.080	30	.003	2.434	.000	.144	73.030	1.000
	$\overline{c_t}$	.048	30	.002	3.096	.000	.176	92.873	1.000
Error	c_t	.478	434	.001					
	$\overline{c_t}$	.223	434	.001					
Total	c_t	302.980	465						
	$\overline{c_t}$	306.070	465						
Corr. Total	c_t	.559	464						
	$\overline{c_t}$	.270	464						

a. R Squared = .144 (Adjusted R Squared = .085)
b. R Squared = .176 (Adjusted R Squared = .119)
c. Computed using alpha = .05

Table S.3 H1: Correlations Using Composite Data Set and Consensus Required [b c]

		f_t	$\overline{f_t}$	t_s
	Spearman's Rho Correlation Coefficient	-.001	-.005	.007
q [a]	Sig. (2-tailed)	.949	.566	.479
	N	11397	11397	11397
	Pearson Correlation	.001	-.003	.009
q [a]	Sig. (2-tailed)	.930	.756	.330
	N	11397	11397	11397

a. Data based on overall composite test of all variables from Hypothesis 1
b. Note that over the widest range tested, the parameter is not significant.
c. Strategies Enabled (Continuous Diversity and Situational Management Strategies)
d. n = (2,3, 6, 7, 10, 11), m = (10, 20, 50), p = (20, 50, 80), q = (20, 50, 80), mdt = [10 5 60], S = 10
**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

Appendix T: Hypothesis 1 Maximum Downtime

Table T.1 H1: Test of Between-Subject Effects for Maximum-Downtime

Source	Dep. Var.	Type III Sum of Squares	df	Mean Square	F	Sig.	η^2	Noncent. Param.	Obs. Power[d]
Corr. Model	f_t	110.211[a]	10	11.021	.578	.834	.001	5.776	.310
	$\overline{f_t}$	1089.939[b]	10	108.994	5.815	.000	.005	58.154	1.000
	t_s	1095570.673[c]	10	109557.067	2.046	.025	.002	20.460	.898
Inter.	f_t	70989820.020	1	70989820.02	3720526.3	.000	.997	3720526.39	1.000
	$\overline{f_t}$	55996113.618	1	55996113.61	2987691.1	.000	.996	2987691.12	1.000
	t_s	1208571887.25	1	1208571887	22570.206	.000	.679	22570.206	1.000
mdt	f_t	110.211	10	11.021	.578	.834	.001	5.776	.310
	$\overline{f_t}$	1089.939	10	108.994	5.815	.000	.005	58.154	1.000
	t_s	1095570.673	10	109557.067	2.046	.025	.002	20.460	.898
Error	f_t	203914.212	10687	19.081					
	$\overline{f_t}$	200298.639	10687	18.742					
	t_s	572259185.814	10687	53547.224					
Total	f_t	71198552.183	10698						
	$\overline{f_t}$	56203314.078	10698						
	t_s	1782233959.00	10698						
Corr. Total	f_t	204024.423	10697						
	$\overline{f_t}$	201388.579	10697						
	t_s	573354756.487	10697						

a. R Squared = .001 (Adjusted R Squared = .000)
b. R Squared = .005 (Adjusted R Squared = .004)
c. R Squared = .002 (Adjusted R Squared = .001)
d. Computed using alpha = .05

Table T.2 H1: Correlations Using Composite Data Set and Consensus Required [b c d]

		f_t	$\overline{f_t}$	t_s
mdt [a]	Spearman's Rho Correlation Coefficient	.005	.048**	.007
	Sig. (2-tailed)	.566	.000	.428
	N	11397	11397	11397
mdt [a]	Pearson Correlation	.006	.050**	.001
	Sig. (2-tailed)	.507	.000	.937
	N	11397	11397	11397

a. Data based on overall composite test of all variables from Hypothesis 1
b. Note that over the wider range tested and strategies tested only average fitness is significant (i.e. strategy changes significance of relationships, specifically management pressure with search times).
c. Strategies Enabled (Continuous Diversity and Situational Management Strategies).
d. n = (2,3, 6, 7, 10, 11), m = (10, 20, 50), p = (20, 50, 80), q = (20, 50, 80), mdt = [10 5 60], S = 10

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

Table T.3 H1: Correlations New Simulation Data Set to Examine Clustering [a b c]

			C_f	$\overline{C}$	$Path\ Length_f$	$\overline{Path\ Length}$
Consensus Not Required	mdt [a]	Spearman's Rho Correlation Coefficient	-.311**	-.410**	.202**	.235**
		Sig. (2-tailed)	.000	.000	.000	.000
		N	800	800	800	800
Consensus Required	mdt [a]	Pearson Correlation	-.261**	-.398**	-.221**	.000
		Sig. (2-tailed)	.000	.000	.000	.999
		N	800	800	800	800
			f_t	$\overline{f_t}$	$\min(f)$	t_s
Consensus Not Required	mdt [a]	Spearman's Rho Correlation Coefficient	.066	.186**	.094**	-.151**
		Sig. (2-tailed)	.064	.000	.008	.000
		N	800	800	800	800
Consensus Required	mdt [a]	Pearson Correlation	.007	.455**	.162**	.067
		Sig. (2-tailed)	.846	.000	.000	.060
		N	800	800	800	800

a. Data based on new simulation to capture the relationship with requisite consensus, average clustering, performance statistics, and path length (note that a final correlation with path length relates to the success rate of the DAU in reaching consensus by the τ = 1000 ticks simulation time limit).

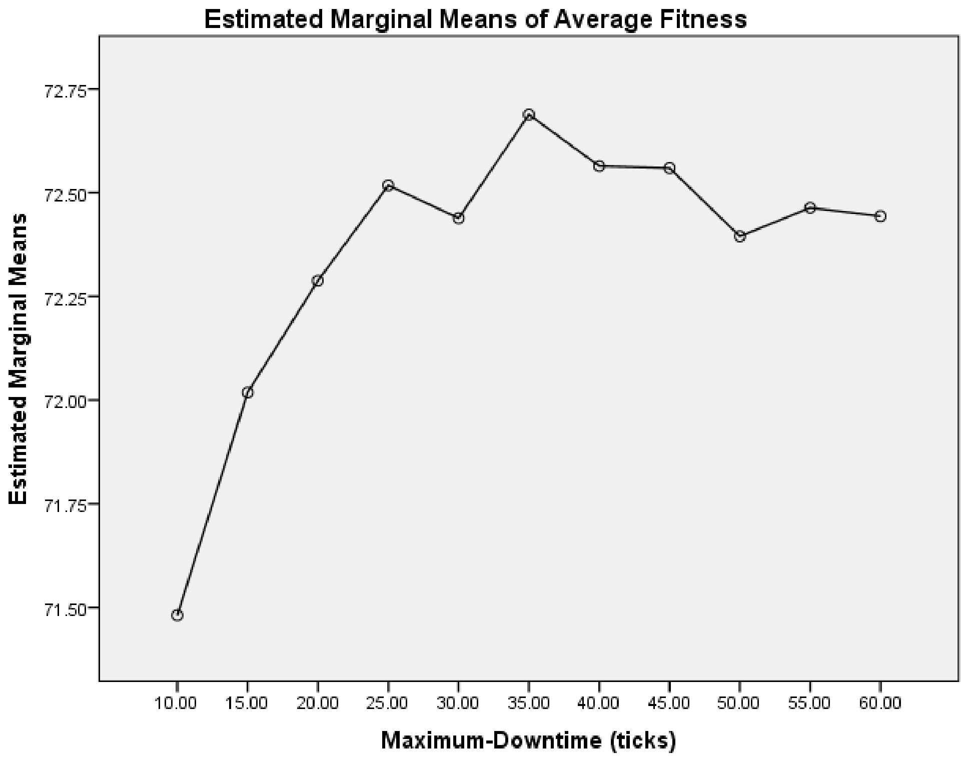
b. Strategies Enabled (Continuous Diversity and Situational Management Strategies).

c. n = 4, m = 30, p = 50, q = 85, mdt = [0 3 45], S = 20

1. Note: The data shows that for mdt greater than approximately nine ticks the relationship begins to level off and significance is only weakly maintained for search-times and average design-team cohesiveness ($\overline{C}$) when consensus is off and for average design-team fitness for when consensus is on.

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).



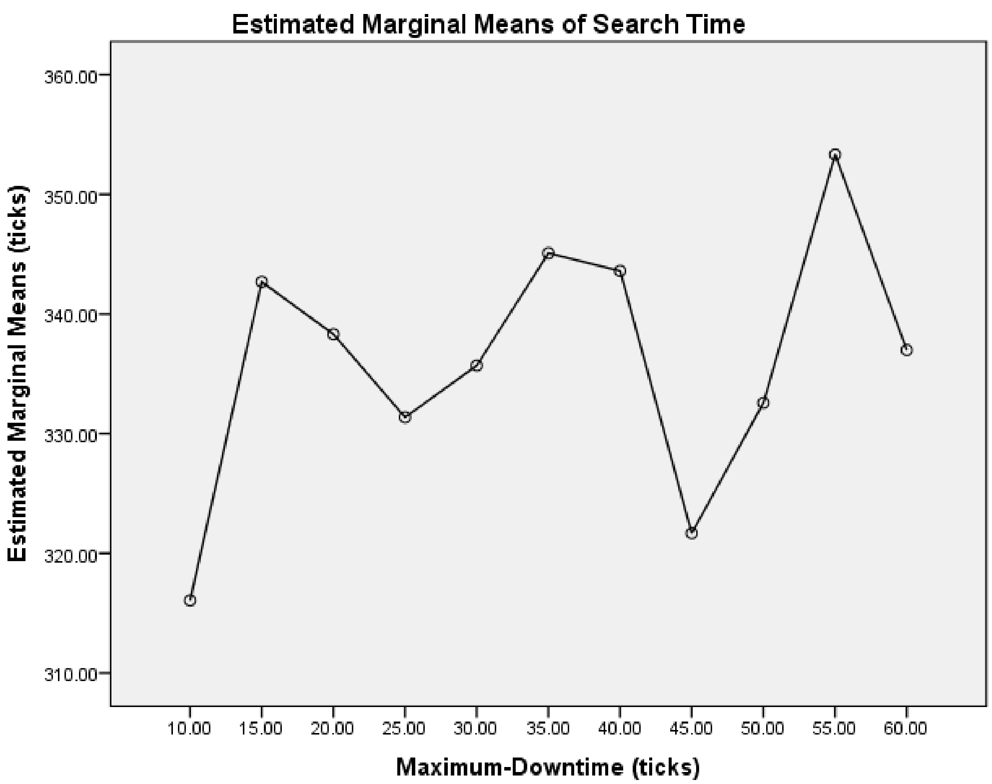


Figure T.1 H1: Estimated Marginal Means for Maximum-Downtime to Performance

APPENDIX U: HYPOTHESIS 2 FINAL FITNESS AND NEWCOMERS

Table U.1 H2: Test of Between Groups Trends for Final Fitness

Final Fitness (f_t)			Sum of Squares	df	Mean Square	F	Sig. [a]
Between Groups	(Combined)		1230.456	30	41.015	.881	.651
	Linear Term	Contrast	.161	1	.161	.003	.953
		Deviation	1230.295	29	42.424	.911	.602
	Quadratic Term	Contrast	207.837	1	207.837	4.464	.035
		Deviation	1022.458	28	36.516	.784	.779
	Cubic Term	Contrast	28.005	1	28.005	.601	.438
		Deviation	994.453	27	36.832	.791	.765
Within Groups			20208.489	434	46.563		
Total			21438.945	464			

a. Using a test of between-subject effects, the observed power is 1.00 for the probability of an incorporating a newcomer (p) and final fitness.

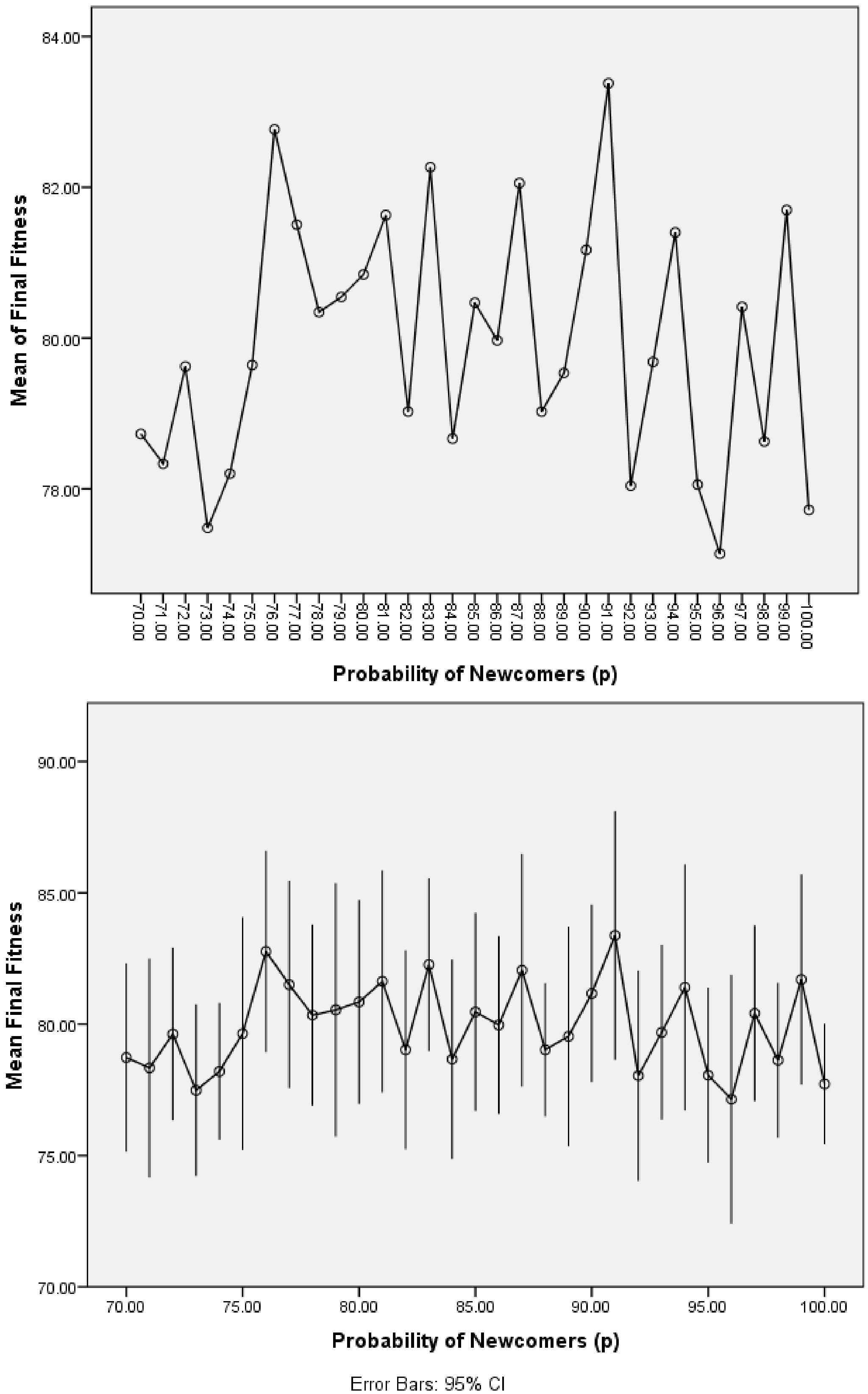


Figure U.1 H2: Estimated Marginal Means for Probability for Newcomer and Mean Final Fitness

Appendix V: Hypothesis 3 Diversity and Performance

Table V.1 H3: Test of Between-Subject Effects for Diversity and Linearity

Source	Dep. Var.	Type III Sum of Squares	df	Mean Square	F	Sig.	η^2	Noncent. Param.	Obs. Power[h]
Corr. Model	f_t	1413.871[a]	13	108.759	3.094	.000	.055	40.217	.996
	$\overline{f_t}$	400.213[b]	13	30.786	1.353	.177	.025	17.587	.784
	t_s	3338259.927[c]	13	256789.225	5.698	.000	.097	74.078	1.000
	f_m	107.502[d]	13	8.269	.402	.969	.008	5.232	.244
	f_t/f_m	.149[e]	13	.011	6.473	.000	.109	84.148	1.000
	$f_m - f_t$	1118.451[f]	13	86.035	6.471	.000	.109	84.125	1.000
	S-Fit	.157[g]	13	.012	.	.	1.00	.	.
Inter.	f_t	4762588.031	1	4762588.031	135471.2	.000	.995	135471.245	1.000
	$\overline{f_t}$	3905973.611	1	3905973.611	171641.6	.000	.996	171641.600	1.000
	t_s	53023885.213	1	53023885.213	1176.633	.000	.632	1176.633	1.000
	f_m	5037760.468	1	5037760.468	245189.9	.000	.997	245189.936	1.000
	f_t/f_m	661.535	1	661.535	373843.1	.000	.998	373843.190	1.000
	$f_m - f_t$	3863.883	1	3863.883	290.623	.000	.298	290.623	1.000
	S-Fit	660.179	1	660.179	.	.	1.00	.	.
m	f_t	1413.871	13	108.759	3.094	.000	.055	40.217	.996
	$\overline{f_t}$	400.213	13	30.786	1.353	.177	.025	17.587	.784
	t_s	3338259.927	13	256789.225	5.698	.000	.097	74.078	1.000
	f_m	107.502	13	8.269	.402	.969	.008	5.232	.244
	f_t/f_m	.149	13	.011	6.473	.000	.109	84.148	1.000
	$f_m - f_t$	1118.451	13	86.035	6.471	.000	.109	84.125	1.000
	S-Fit	.157	13	.012	.	.	1.00	.	.
Error	f_t	24116.818	686	35.156					
	$\overline{f_t}$	15611.005	686	22.757					
	t_s	30913957.860	686	45064.079					
	f_m	14094.802	686	20.546					
	f_t/f_m	1.214	686	.002					
	$f_m - f_t$	9120.479	686	13.295					
	S-Fit	.000	686	.000					
Total	f_t	4788118.720	700						

Table V.1 H3: Test of Between-Subject Effects for Diversity (Continued)

Total (Cont'd)	$\overline{f_t}$	3921984.829	700						
	t_s	87276103.000	700						
	f_m	5051962.773	700						
	f_t/f_m	662.898	700						
	$f_m - f_t$	14102.813	700						
	S-Fit	660.335	700						
Corr. Total	f_t	25530.689	699						
	$\overline{f_t}$	16011.218	699						
	t_s	34252217.787	699						
	f_m	14202.304	699						
	f_t/f_m	1.363	699						
	$f_m - f_t$	10238.930	699						
	S-Fit	.157	699						

a. R Squared = .055 (Adjusted R Squared = .037)
b. R Squared = .025 (Adjusted R Squared = .007)
c. R Squared = .097 (Adjusted R Squared = .080)
d. R Squared = .008 (Adjusted R Squared = -.011)
e. R Squared = .109 (Adjusted R Squared = .092)
f. R Squared = .109 (Adjusted R Squared = .092)
g. R Squared = 1.000 (Adjusted R Squared = 1.000)
h. Computed using alpha = .05

Table V.2 H3: Analysis of Variances (ANOVA) Among Trends

DV $\ln(f_t\ /f_m)$ and IV $(1\ /m)$			Sum of Squares	df	Mean Square	F (13, 313)	Sig.
Between Groups	(Combined)		.136	13	.010	3.726	.000
	Linear Term	Weighted	.128	1	.128	45.647	.000
		Deviation	.008	12	.001	.233	.997
	Quadratic Term	Weighted	.001	1	.001	.325	.569
		Deviation	.007	11	.001	.225	.996
	Cubic Term	Weighted	.000	1	.000	.059	.809
		Deviation	.007	10	.001	.241	.992
	4th-order Term	Weighted	.000	1	.000	.018	.892
		Deviation	.007	9	.001	.266	.983
	5th-order Term	Weighted	.000	1	.000	.008	.927
		Deviation	.007	8	.001	.298	.966
	Within Groups		.880	313	.003		
Total			1.016	326			

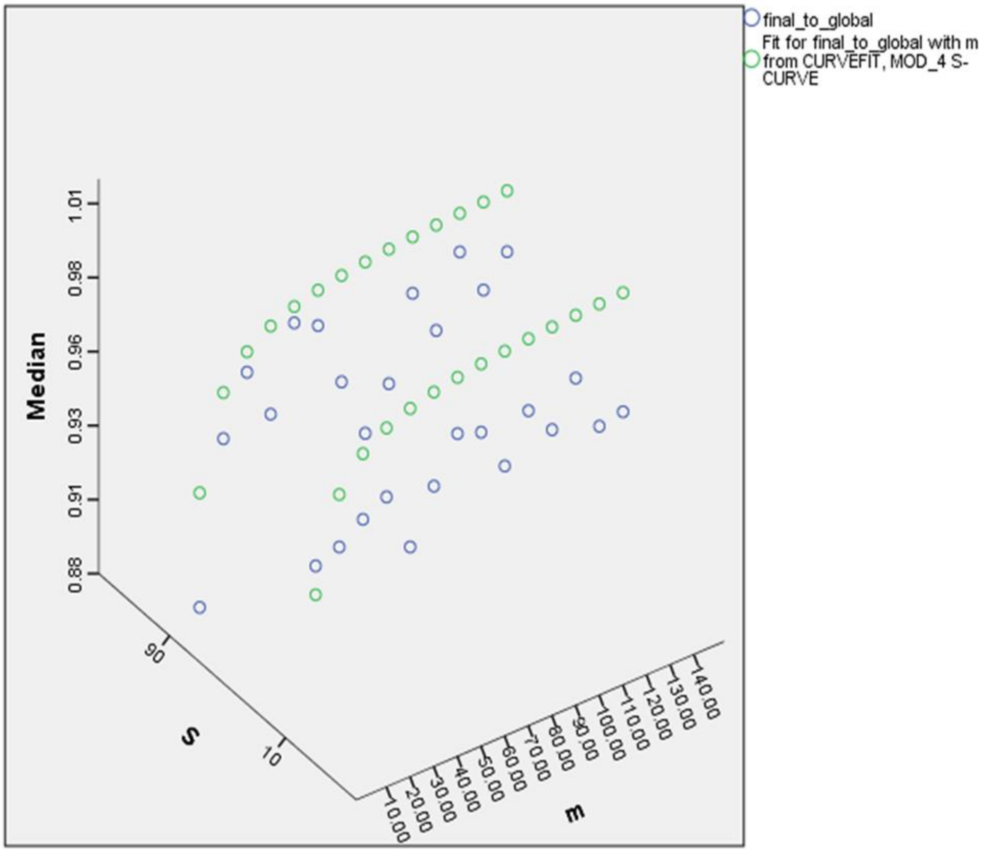


Figure V.1 Final to Global for Different Smoothness and Values of Allowable Diversity

Table V.3 H3: Between Subject Effects for 30 $< m <$ 140

Source	Dep. Var.	Type III Sum of Squares	df	Mean Square	F	Sig.	η^2	Noncent. Param.	Obs. Power[h]
m	t_s	204662.757	12	17055.230	.392	.966	.017	4.701	.223
	f_t	188.700	12	15.725	1.030	.421	.045	12.364	.596
	$\overline{f_t}$	151.129	12	12.594	.923	.524	.040	11.081	.537
	f_t/f_m	.033	12	.003	1.840	.042	.077	22.083	.890

APPENDIX W: HYPOTHESIS 4 TEAM-SIZE AND PERFORMANCE

Table W.1 H4: Test of Between-Subject Effects for Team-Sizes with S = 0%

S	Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Noncent. Parameter	Obs. Power[e]
S= 0%	Corrected Model	$f_t\ /f_m$	.159[a]	11	.014	1.280	.235	14.078	.689
		$\max(f_t)\ /f_m$	.069[b]	11	.006	2.614	.003	28.757	.970
		$\overline{f_t}\ /f_m$	.073[c]	11	.007	3.365	.000	37.017	.994
		$\overline{P} = \overline{f_t}\ /(n * t_s)$	183.367[d]	11	16.670	19.917	.000	219.091	1.000
	Intercept	$f_t\ /f_m$	195.996	1	195.996	17391.872	.000	17391.872	1.000
		$\max(f_t)\ /f_m$	249.813	1	249.813	104705.954	.000	104705.954	1.000
		$\overline{f_t}\ /f_m$	177.518	1	177.518	90031.852	.000	90031.852	1.000
		$\overline{P} = \overline{f_t}\ /(n * t_s)$	335.129	1	335.129	400.420	.000	400.420	1.000
	n	$f_t\ /f_m$	.159	11	.014	1.280	.235	14.078	.689
		$\max(f_t)\ /f_m$	.069	11	.006	2.614	.003	28.757	.970
		$\overline{f_t}\ /f_m$	.073	11	.007	3.365	.000	37.017	.994
		$\overline{P} = \overline{f_t}\ /(n * t_s)$	183.367	11	16.670	19.917	.000	219.091	1.000
	Error	$f_t\ /f_m$	3.246	288	.011				
		$\max(f_t)\ /f_m$	.687	288	.002				
		$\overline{f_t}\ /f_m$	.568	288	.002				
		$\overline{P} = \overline{f_t}\ /(n * t_s)$	241.040	288	.837				
	Total	$f_t\ /f_m$	199.400	300					
		$\max(f_t)\ /f_m$	250.568	300					
		$\overline{f_t}\ /f_m$	178.159	300					
		$\overline{P} = \overline{f_t}\ /(n * t_s)$	759.537	300					
	Corrected Total	$f_t\ /f_m$	3.404	299					
		$\max(f_t)\ /f_m$	.756	299					
		$\overline{f_t}\ /f_m$	.641	299					
		$\overline{P} = \overline{f_t}\ /(n * t_s)$	424.407	299					

a. R Squared = .047 (Adjusted R Squared = .010)

b. R Squared = .091 (Adjusted R Squared = .056)

c. R Squared = .114 (Adjusted R Squared = .080)

d. R Squared = .432 (Adjusted R Squared = .410)

e. Computed using alpha = .05

f. The $\max(f_t)\ /f_m$ corresponds to the maximum value achieved relative to the global maximum.

Table W.2 H4: Test of Between-Subject Effects for Team-Sizes with S = 20%

S	Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Noncent. Parameter	Obs. Power[e]
S = 20%	Corrected Model	f_t/f_m	.097[a]	11	.009	.977	.467	10.752	.543
		$\max(f_t)/f_m$	.023[b]	11	.002	1.839	.047	20.225	.869
		$\overline{f_t}/f_m$	.252[c]	11	.023	13.088	.000	143.965	1.000
		$\overline{P}=\overline{f_t}/(n*t_s)$	2282.104[d]	11	207.464	8.852	.000	97.374	1.000
	Intercept	f_t/f_m	249.968	1	249.968	27647.479	.000	27647.479	1.000
		$\max(f_t)/f_m$	281.659	1	281.659	251943.811	.000	251943.811	1.000
		$\overline{f_t}/f_m$	209.399	1	209.399	119540.756	.000	119540.756	1.000
		$\overline{P}=\overline{f_t}/(n*t_s)$	1422.946	1	1422.946	60.715	.000	60.715	1.000
	n	f_t/f_m	.097	11	.009	.977	.467	10.752	.543
		$\max(f_t)/f_m$	.023	11	.002	1.839	.047	20.225	.869
		$\overline{f_t}/f_m$	.252	11	.023	13.088	.000	143.965	1.000
		$\overline{P}=\overline{f_t}/(n*t_s)$	2282.104	11	207.464	8.852	.000	97.374	1.000
	Error	f_t/f_m	2.604	288	.009				
		$\max(f_t)/f_m$	.322	288	.001				
		$\overline{f_t}/f_m$	.504	288	.002				
		$\overline{P}=\overline{f_t}/(n*t_s)$	6749.675	288	23.436				
	Total	f_t/f_m	252.669	300					
		$\max(f_t)/f_m$	282.004	300					
		$\overline{f_t}/f_m$	210.155	300					
		$\overline{P}=\overline{f_t}/(n*t_s)$	10454.726	300					
	Corrected Total	f_t/f_m	2.701	299					
		$\max(f_t)/f_m$	.345	299					
		$\overline{f_t}/f_m$	.757	299					
		$\overline{P}=\overline{f_t}/(n*t_s)$	9031.780	299					

a. R Squared = .036 (Adjusted R Squared = -.001)

b. R Squared = .066 (Adjusted R Squared = .030)

c. R Squared = .333 (Adjusted R Squared = .308)

d. R Squared = .253 (Adjusted R Squared = .224)

e. Computed using alpha = .05

Table W.3 H4: Test of Between-Subject Effects for Team-Sizes with S = 40%

S	Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Noncent. Parameter	Obs. Power[e]
S= 40%	Corrected Model	f_t / f_m	.051[a]	11	.005	.713	.726	7.843	.395
		$\max(f_t) / f_m$	.016[b]	11	.001	2.147	.017	23.612	.924
		$\overline{f_t} / f_m$	.260[c]	11	.024	13.045	.000	143.500	1.000
		$\overline{P} = \overline{f_t} / (n * t_s)$	2103.739[d]	11	191.249	26.123	.000	287.358	1.000
	Intercept	f_t / f_m	269.677	1	269.677	41678.085	.000	41678.085	1.000
		$\max(f_t) / f_m$	289.028	1	289.028	437395.246	.000	437395.246	1.000
		$\overline{f_t} / f_m$	215.841	1	215.841	119214.653	.000	119214.653	1.000
		$\overline{P} = \overline{f_t} / (n * t_s)$	1818.021	1	1818.021	248.331	.000	248.331	1.000
	n	f_t / f_m	.051	11	.005	.713	.726	7.843	.395
		$\max(f_t) / f_m$	.016	11	.001	2.147	.017	23.612	.924
		$\overline{f_t} / f_m$	.260	11	.024	13.045	.000	143.500	1.000
		$\overline{P} = \overline{f_t} / (n * t_s)$	2103.739	11	191.249	26.123	.000	287.358	1.000
	Error	f_t / f_m	1.863	288	.006				
		$\max(f_t) / f_m$	.190	288	.001				
		$\overline{f_t} / f_m$	.521	288	.002				
		$\overline{P} = \overline{f_t} / (n * t_s)$	2108.437	288	7.321				
	Total	f_t / f_m	271.591	300					
		$\max(f_t) / f_m$	289.234	300					
		$\overline{f_t} / f_m$	216.622	300					
		$\overline{P} = \overline{f_t} / (n * t_s)$	6030.197	300					
	Corrected Total	f_t / f_m	1.914	299					
		$\max(f_t) / f_m$	.206	299					
		$\overline{f_t} / f_m$	.781	299					
		$\overline{P} = \overline{f_t} / (n * t_s)$	4212.176	299					

a. R Squared = .027 (Adjusted R Squared = -.011)

b. R Squared = .076 (Adjusted R Squared = .040)

c. R Squared = .333 (Adjusted R Squared = .307)

d. R Squared = .499 (Adjusted R Squared = .480)

e. Computed using alpha = .05

Table W.4 H4: Test of Between-Subject Effects for Team-Sizes with S = 60%

S	Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Noncent. Parameter	Obs. Power[e]
S = 60%	Corrected Model	f_t / f_m	.043a	11	.004	.684	.754	7.521	.378
		$\max(f_t) / f_m$	.007[b]	11	.001	1.522	.123	16.744	.781
		$\overline{f_t} / f_m$	.398[c]	11	.036	22.088	.000	242.963	1.000
		$\overline{P} = \overline{f_t} / (n * t_s)$	2680.134[d]	11	243.649	24.847	.000	273.312	1.000
	Intercept	f_t / f_m	274.406	1	274.406	47738.762	.000	47738.762	1.000
		$\max(f_t) / f_m$	291.606	1	291.606	708418.711	.000	708418.711	1.000
		$\overline{f_t} / f_m$	218.732	1	218.732	133479.937	.000	133479.937	1.000
		$\overline{P} = \overline{f_t} / (n * t_s)$	2092.842	1	2092.842	213.422	.000	213.422	1.000
	n	f_t / f_m	.043	11	.004	.684	.754	7.521	.378
		$\max(f_t) / f_m$	.007	11	.001	1.522	.123	16.744	.781
		$\overline{f_t} / f_m$	.398	11	.036	22.088	.000	242.963	1.000
		$\overline{P} = \overline{f_t} / (n * t_s)$	2680.134	11	243.649	24.847	.000	273.312	1.000
	Error	f_t / f_m	1.655	288	.006				
		$\max(f_t) / f_m$	.119	288	.000				
		$\overline{f_t} / f_m$	.472	288	.002				
		$\overline{P} = \overline{f_t} / (n * t_s)$	2824.166	288	9.806				
	Total	f_t / f_m	276.105	300					
		$\max(f_t) / f_m$	291.732	300					
		$\overline{f_t} / f_m$	219.602	300					
		$\overline{P} = \overline{f_t} / (n * t_s)$	7597.142	300					
	Corrected Total	f_t / f_m	1.699	299					
		$\max(f_t) / f_m$	.125	299					
		$\overline{f_t} / f_m$	.870	299					
		$\overline{P} = \overline{f_t} / (n * t_s)$	5504.300	299					

a. R Squared = .025 (Adjusted R Squared = -.012)

b. R Squared = .055 (Adjusted R Squared = .019)

c. R Squared = .458 (Adjusted R Squared = .437)

d. R Squared = .487 (Adjusted R Squared = .467)

e. Computed using alpha = .05

Table W.5 H4: Test of Between-Subject Effects for Team-Sizes with S = 80%

S	Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Noncent. Parameter	Obs. Power[e]
S = 80%	Corrected Model	$f_t\ /f_m$	.027[a]	11	.002	.869	.571	9.558	.484
		$\max(f_t)\ /f_m$	.007[b]	11	.001	1.759	.061	19.354	.850
		$\overline{f_t}\ /f_m$	.445[c]	11	.040	21.412	.000	235.536	1.000
		$\overline{P} = \overline{f_t}\ /(n * t_s)$	4816.036[d]	11	437.821	27.189	.000	299.080	1.000
	Intercept	$f_t\ /f_m$	283.542	1	283.542	99181.611	.000	99181.611	1.000
		$\max(f_t)\ /f_m$	293.329	1	293.329	849865.613	.000	849865.613	1.000
		$\overline{f_t}\ /f_m$	216.321	1	216.321	114490.040	.000	114490.040	1.000
		$\overline{P} = \overline{f_t}\ /(n * t_s)$	3696.024	1	3696.024	229.527	.000	229.527	1.000
	n	$f_t\ /f_m$	.027	11	.002	.869	.571	9.558	.484
		$\max(f_t)\ /f_m$	.007	11	.001	1.759	.061	19.354	.850
		$\overline{f_t}\ /f_m$	.445	11	.040	21.412	.000	235.536	1.000
		$\overline{P} = \overline{f_t}\ /(n * t_s)$	4816.036	11	437.821	27.189	.000	299.080	1.000
	Error	$f_t\ /f_m$	.823	288	.003				
		$\max(f_t)\ /f_m$	.099	288	.000				
		$\overline{f_t}\ /f_m$	.544	288	.002				
		$\overline{P} = \overline{f_t}\ /(n * t_s)$	4637.609	288	16.103				
	Total	$f_t\ /f_m$	284.393	300					
		$\max(f_t)\ /f_m$	293.435	300					
		$\overline{f_t}\ /f_m$	217.310	300					
		$\overline{P} = \overline{f_t}\ /(n * t_s)$	13149.668	300					
	Corrected Total	$f_t\ /f_m$	.851	299					
		$\max(f_t)\ /f_m$	.106	299					
		$\overline{f_t}\ /f_m$	.989	299					
		$\overline{P} = \overline{f_t}\ /(n * t_s)$	9453.645	299					

a. R Squared = .032 (Adjusted R Squared = -.005)

b. R Squared = .063 (Adjusted R Squared = .027)

c. R Squared = .450 (Adjusted R Squared = .429)

d. R Squared = .509 (Adjusted R Squared = .491)

e. Computed using alpha = .05

Table W.6 H4: Test of Between-Subject Effects for Team-Sizes with S = 100%

S	Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Noncent. Parameter	Obs. Power[d]
S = 100%	Corrected Model	f_t / f_m	.000[a]	11	4.120E-005	1.076	.381	11.832	.594
		$\max(f_t) / f_m$	.000[a]	11	4.120E-005	1.076	.381	11.832	.594
		$\overline{f_t} / f_m$	.175[b]	11	.016	4.735	.000	52.081	1.000
		$\overline{P} = \overline{f_t} / (n * t_s)$	23260.548[c]	11	2114.595	41.217	.000	453.382	1.000
	Intercept	f_t / f_m	294.181	1	294.181	7681197.733	.000	7681197.733	1.000
		$\max(f_t) / f_m$	294.181	1	294.181	7681197.733	.000	7681197.733	1.000
		$\overline{f_t} / f_m$	188.645	1	188.645	56073.104	.000	56073.104	1.000
		$\overline{P} = \overline{f_t} / (n * t_s)$	19890.671	1	19890.671	387.698	.000	387.698	1.000
	n	f_t / f_m	.000	11	4.120E-005	1.076	.381	11.832	.594
		$\max(f_t) / f_m$	.000	11	4.120E-005	1.076	.381	11.832	.594
		$\overline{f_t} / f_m$	.175	11	.016	4.735	.000	52.081	1.000
		$\overline{P} = \overline{f_t} / (n * t_s)$	23260.548	11	2114.595	41.217	.000	453.382	1.000
	Error	f_t / f_m	.011	288	3.830E-005				
		$\max(f_t) / f_m$	.011	288	3.830E-005				
		$\overline{f_t} / f_m$	.969	288	.003				
		$\overline{P} = \overline{f_t} / (n * t_s)$	14775.697	288	51.305				
	Total	f_t / f_m	294.192	300					
		$\max(f_t) / f_m$	294.192	300					
		$\overline{f_t} / f_m$	189.789	300					
		$\overline{P} = \overline{f_t} / (n * t_s)$	57926.917	300					
	Corrected Total	f_t / f_m	.011	299					
		$\max(f_t) / f_m$	.011	299					
		$\overline{f_t} / f_m$	1.144	299					
		$\overline{P} = \overline{f_t} / (n * t_s)$	38036.246	299					

a. R Squared = .039 (Adjusted R Squared = .003)

b. R Squared = .153 (Adjusted R Squared = .121)

c. R Squared = .612 (Adjusted R Squared = .597)

d. Computed using alpha = .05

Table W.7 H4: Spearman’s Rho Correlations

Correlations

S				n	Productivity_Labor_Average
0	Kendall's tau_b	n	Correlation Coefficient	1.000	-.907**
			Sig. (2-tailed)	.	.000
			N	300	300
		Productivity_Labor_Average	Correlation Coefficient	-.907**	1.000
			Sig. (2-tailed)	.000	.
			N	300	300
	Spearman's rho	n	Correlation Coefficient	1.000	-.980**
			Sig. (2-tailed)	.	.000
			N	300	300
		Productivity_Labor_Average	Correlation Coefficient	-.980**	1.000
			Sig. (2-tailed)	.000	.
			N	300	300
20	Kendall's tau_b	n	Correlation Coefficient	1.000	-.802**
			Sig. (2-tailed)	.	.000
			N	300	300
		Productivity_Labor_Average	Correlation Coefficient	-.802**	1.000
			Sig. (2-tailed)	.000	.
			N	300	300
	Spearman's rho	n	Correlation Coefficient	1.000	-.917**
			Sig. (2-tailed)	.	.000
			N	300	300
		Productivity_Labor_Average	Correlation Coefficient	-.917**	1.000
			Sig. (2-tailed)	.000	.
			N	300	300
40	Kendall's tau_b	n	Correlation Coefficient	1.000	-.724**
			Sig. (2-tailed)	.	.000
			N	300	300
		Productivity_Labor_Average	Correlation Coefficient	-.724**	1.000
			Sig. (2-tailed)	.000	.
			N	300	300
	Spearman's rho	n	Correlation Coefficient	1.000	-.873**
			Sig. (2-tailed)	.	.000
			N	300	300
		Productivity_Labor_Average	Correlation Coefficient	-.873**	1.000
			Sig. (2-tailed)	.000	.
			N	300	300
60	Kendall's tau_b	n	Correlation Coefficient	1.000	-.694**
			Sig. (2-tailed)	.	.000
			N	300	300
		Productivity_Labor_Average	Correlation Coefficient	-.694**	1.000
			Sig. (2-tailed)	.000	.
			N	300	300
	Spearman's rho	n	Correlation Coefficient	1.000	-.849**
			Sig. (2-tailed)	.	.000
			N	300	300
		Productivity_Labor_Average	Correlation Coefficient	-.849**	1.000
			Sig. (2-tailed)	.000	.
			N	300	300
80	Kendall's tau_b	n	Correlation Coefficient	1.000	-.643**
			Sig. (2-tailed)	.	.000
			N	300	300
		Productivity_Labor_Average	Correlation Coefficient	-.643**	1.000
			Sig. (2-tailed)	.000	.
			N	300	300
	Spearman's rho	n	Correlation Coefficient	1.000	-.808**
			Sig. (2-tailed)	.	.000
			N	300	300
		Productivity_Labor_Average	Correlation Coefficient	-.808**	1.000
			Sig. (2-tailed)	.000	.
			N	300	300
100	Kendall's tau_b	n	Correlation Coefficient	1.000	-.772**
			Sig. (2-tailed)	.	.000
			N	300	300
		Productivity_Labor_Average	Correlation Coefficient	-.772**	1.000
			Sig. (2-tailed)	.000	.
			N	300	300
	Spearman's rho	n	Correlation Coefficient	1.000	-.918**
			Sig. (2-tailed)	.	.000
			N	300	300
		Productivity_Labor_Average	Correlation Coefficient	-.918**	1.000
			Sig. (2-tailed)	.000	.
			N	300	300

**. Correlation is significant at the 0.01 level (2-tailed).

Table W.8 H4: Correlations of Team-Size

Correlations

			Team-Size (n)	Marginal Productivity
Spearman's Rho (ρ)	Team-size (n)	Correlation Coefficient	1.000	-.646**
		Sig. (2-tailed)	.	.000
		N	1751	1751
	Marginal Productivity	Correlation Coefficient	-.646**	1.000
		Sig. (2-tailed)	.000	.
		N	1751	1751

**. Correlation is significant at the 0.01 level (2-tailed).

APPENDIX X: HYPOTHESIS 5 NEWCOMERS AND PERFORMANCE

Table X.1 H5: Test of Between-Subject Effects for Probability of Incorporating a Newcomer Test

Source	Dep. Var. [d]	Type III Sum of Squares	df	Mean Square	F	Sig.	η^2	Noncent. Param.	Obs. Power[c]
Corrected Model	$\overline{f_t}$	7971.772[a]	25	318.871	12.691	.000	.110	317.263	1.00
	t_s	15914204.542[b]	25	636568.182	10.257	.000	.091	256.428	1.00
Intercept	$\overline{f_t}$	14046579.790	1	14046560.725	559028.55	.000	.995	559028.5	1.000
	t_s	260161812.578	1	260161812.57	4192.026	.000	.620	4192.026	1.000
p	$\overline{f_t}$	2078.661	12	173.222	6.894	.000	.031	82.727	1.000
	t_s	1530474.422	12	127539.535	2.055	.017	.009	24.661	.937
S	$\overline{f_t}$	5732.371	1	5732.376	228.139	.000	.081	228.139	1.000
	t_s	14100587.225	1	14100587.225	227.205	.000	.081	227.205	1.000
p * S	$\overline{f_t}$	160.741	12	13.395	.533	.894	.002	6.397	.316
	t_s	283142.895	12	23595.241	.380	.971	.002	4.562	.224
Error	$\overline{f_t}$	64676.218	2574	25.127					
	t_s	159745326.880	2574	62061.122					
Total	$\overline{f_t}$	14119227.781	2600						
	t_s	435821344.000	2600						
Corrected Total	$\overline{f_t}$	72647.991	2599						
	t_s	175659531.422	2599						

a. R Squared = .110 (Adjusted R Squared = .101)
b. R Squared = .091 (Adjusted R Squared = .082)
c. Computed using alpha = .05
d. Fitness variables measured relative to global maximum fitness (f_m)

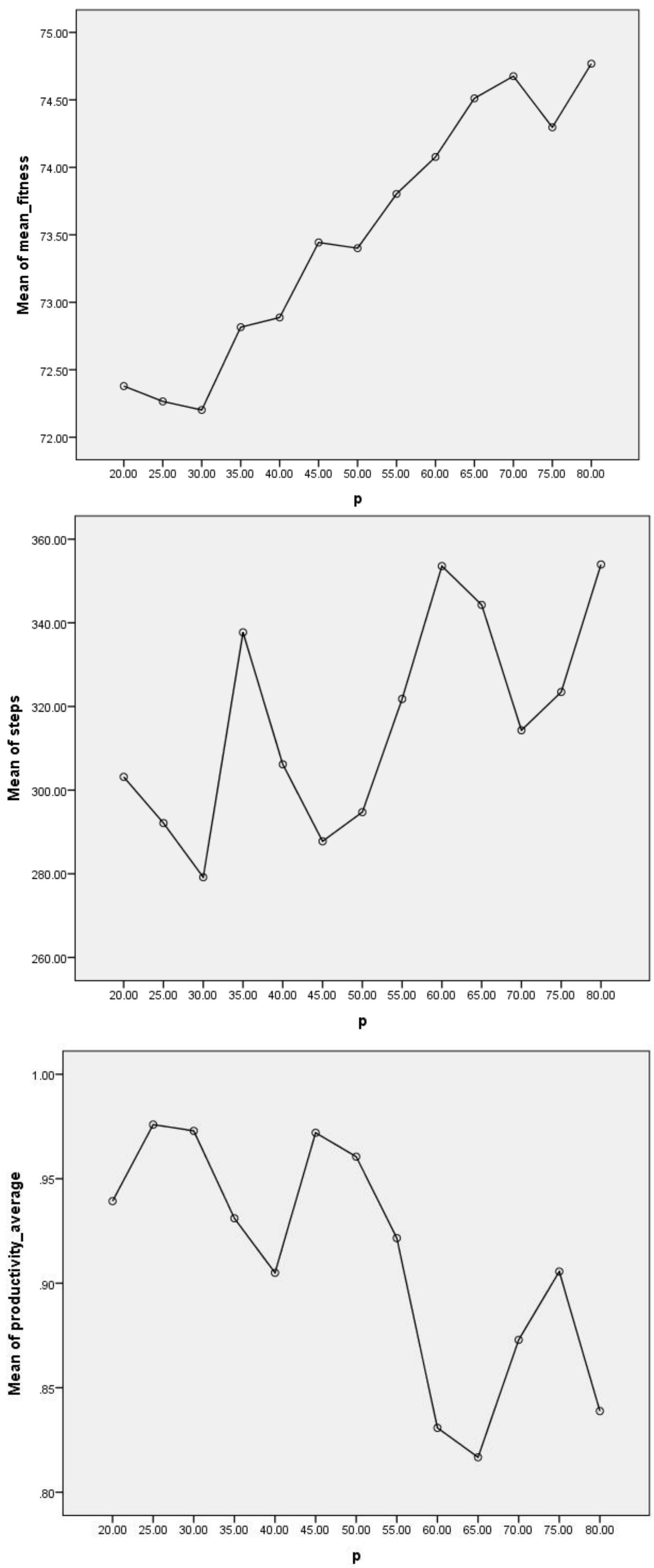


Figure X.1 H5: Marginal Means Plots for Newcomers

APPENDIX Y: HYPOTHESIS 7 CONTINUOUS DIVERSITY STRATEGY

Table Y.1 H7: Descriptive Statistics

		N	Mean	Std. Deviation	Min.	Max.	Percentiles 25th	Percentiles 50th (Median)	Percentiles 75th
Strategy On	f_t	2160	80.0152	5.10571	67.88	100.00	76.2504	79.5510	83.2474
	$max\ f_t$	2160	80.3598	5.07257	67.88	100.00	76.6260	80.0373	83.6913
	$\overline{f_t}$	2160	70.6734	7.11665	52.27	99.17	65.1205	70.1449	76.1028
	t_s	2160	261.9866	324.61214	1.00	1000.00	25.0000	115.0000	359.0000
	$\overline{C}$ (Avg. Clustering)	2160	.8655	.07162	.72	1.00	.8023	.8444	.9401
	$\overline{Path\ Length}$	2160	23.2473	8.44249	2.73	43.98	16.5050	23.2234	30.0928
	C (Final Clustering)	2160	.8575	.08483	.60	1.00	.7863	.8578	.9379
	$Final\ Path\ Length$	2160	14.8793	13.85403	.00	41.63	.0000	15.3744	27.8820
	$\overline{P}$ (Avg. Productivity)	2160	2.4534	4.88798	.07	66.69	.2065	.6285	2.6680
	P (Final Productivity)	2160	2.9040	5.68749	.07	74.84	.2319	.7094	3.2108
Strategy Off	f_t	2160	78.0278	6.54171	54.37	100.00	74.1253	78.1035	82.2980
	$max\ f_t$	2160	79.2509	5.37346	65.05	100.00	75.4540	78.6445	82.7866
	$\overline{f_t}$	2160	71.0482	6.67963	50.61	98.67	65.9262	70.5752	75.9467
	t_s	2160	388.1454	402.21926	1.00	1000.00	33.0000	185.0000	1000.000
	$\overline{C}$ (Avg. Clustering)	2160	.8771	.07067	.73	1.00	.8111	.9069	.9430
	$\overline{Path\ Length}$	2160	18.5824	10.11218	.00	43.07	10.4401	18.0146	26.3729
	C (Final Clustering)	2160	.8715	.08210	.60	1.00	.8033	.8935	.9443
	$Final\ Path\ Length$	2160	10.2667	12.69900	.00	43.10	.0000	.9978	22.7715
	$\overline{P}$ (Avg. Productivity)	2160	2.3429	5.30635	.05	70.32	.0807	.4021	1.9954
	P (Final Productivity)	2160	2.7559	6.20413	.05	83.27	.0838	.4391	2.3784

Table Y.2 H7: Wilcoxon Statistical Significance Results (Strategy as a Treatment)

Value when Strategy is Off – Value when Strategy is On	Final Fitness	Max Fitness	Mean Fitness	Steps	Average Clustering Coeff.	Average Path Length	Final Clustering Coeff.	Final Path Length	Average Productivity	Final Productivity
Z	-11.882[b]	-8.374[b]	-2.456[c]	-9.402[c]	-6.699[c]	-24.283[b]	-6.086[c]	-31.398[b]	-4.228[b]	-4.511[b]
Asymp. Sig. (2-tailed)	.000	.000	.014	.000	.000	.000	.000	.000	.000	.000

a. Wilcoxon Signed Ranks Test

b. Based on positive ranks.

c. Based on negative ranks.

Table Y.3 H7: Test of between Subject Effects between Diversity Strategy and Performance

Source	Dep. Var. [f]	Type III Sum of Squares	df	Mean Square	F (1, 1018)	Sig.	η^2	Noncent. Param.	Obs. Power[e]
Corr. Model	f_t	1388.156[a]	1	1388.156	42.401	.000	.040	42.401	1.000
	$maxf_t$	681.351[b]	1	681.351	24.528	.000	.024	24.528	.999
	$\overline{f_t}$	782.239[c]	1	782.239	17.204	.000	.017	17.204	.986
	t_s	18221427.190[d]	1	18221427.2	170.01	.000	.143	170.012	1.000
Intercept	f_t	6349779.723	1	6349779.72	193953	.000	.995	193953.47	1.000
	$maxf_t$	6438835.384	1	6438835.38	231796	.000	.996	231795.99	1.000
	$\overline{f_t}$	5060333.141	1	5060333.14	111296	.000	.991	111295.61	1.000
	t_s	96859310.068	1	96859310.1	903.73	.000	.470	903.728	1.000
Strategy	f_t	1388.156	1	1388.156	42.401	.000	.040	42.401	1.000
	$maxf_t$	681.351	1	681.351	24.528	.000	.024	24.528	.999
	$\overline{f_t}$	782.239	1	782.239	17.204	.000	.017	17.204	.986
	t_s	18221427.190	1	18221427.2	170.01	.000	.143	170.012	1.000
Error	f_t	33327.971	1018	32.739					
	$maxf_t$	28278.031	1018	27.778					
	$\overline{f_t}$	46285.914	1018	45.467					
	t_s	109106678.79	1018	107177.484					
Total	f_t	6417632.220	1020						
	$maxf_t$	6497973.638	1020						
	$\overline{f_t}$	5117547.057	1020						
	t_s	219627383.00	1020						
Corrected Total	f_t	34716.127	1019						
	$maxf_t$	28959.382	1019						
	$\overline{f_t}$	47068.153	1019						
	t_s	127328105.98	1019						

a. R Squared = .040 (Adjusted R Squared = .039)

b. R Squared = .024 (Adjusted R Squared = .023)

c. R Squared = .017 (Adjusted R Squared = .016)

d. R Squared = .143 (Adjusted R Squared = .142)

f. Computed using alpha = .05

Appendix Z: Hypothesis 8 Talent Retention

Table Z.1 H8: Test of Between Subject Effects for Maximum-Downtime

Source	Dep. Var. [f]	Type III Sum of Squares	df	Mean Square	F (1, 1019)	Sig.	Noncent. Param.	Obs. Power[e]
Corrected Model	f_t	.041[a]	18	.002	1.973	.010	35.509	.979
	$maxf_t$	492.988[b]	18	27.388	1.547	.069	27.846	.926
	$\overline{f_t}$	.058[c]	18	.003	1.339	.157	24.108	.873
	t_s	1770812.425[d]	18	98378.468	1.905	.014	34.286	.974
Intercept	f_t	544.080	1	544.080	475104.558	.000	475104.558	1.000
	$maxf_t$	4058244.301	1	4058244.301	229224.898	.000	229224.898	1.000
	$\overline{f_t}$	426.409	1	426.409	178447.604	.000	178447.604	1.000
	t_s	45795740.975	1	45795740.98	886.677	.000	886.677	1.000
mdt	f_t	.041	18	.002	1.973	.010	35.509	.979
	$maxf_t$	492.988	18	27.388	1.547	.069	27.846	.926
	$\overline{f_t}$	.058	18	.003	1.339	.157	24.108	.873
	t_s	1770812.425	18	98378.468	1.905	.014	34.286	.974
Error	f_t	.631	551	.001				
	$maxf_t$	9755.016	551	17.704				
	$\overline{f_t}$	1.317	551	.002				
	t_s	28458458.600	551	51648.745				
Total	f_t	544.752	570					
	$maxf_t$	4068492.306	570					
	$\overline{f_t}$	427.783	570					
	t_s	76025012.000	570					
Corrected Total	f_t	.672	569					
	$maxf_t$	10248.005	569					
	$\overline{f_t}$	1.374	569					
	t_s	30229271.025	569					

a. R Squared = .061 (Adjusted R Squared = .030)

b. R Squared = .048 (Adjusted R Squared = .017)

c. R Squared = .042 (Adjusted R Squared = .011)

d. R Squared = .059 (Adjusted R Squared = .028)

e. Computed using alpha = .05

f. Fitness variables measured relative to global maximum fitness (f_m)

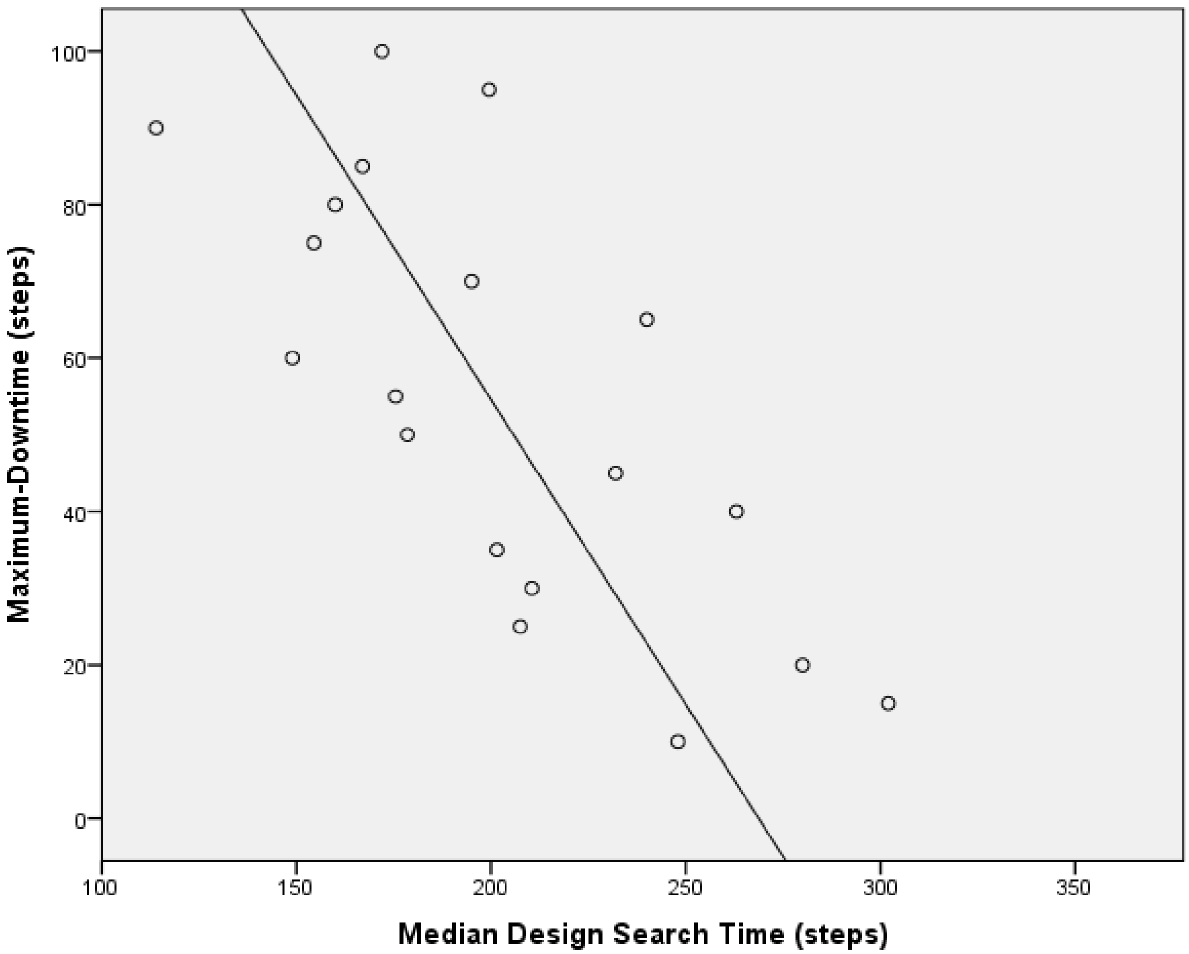
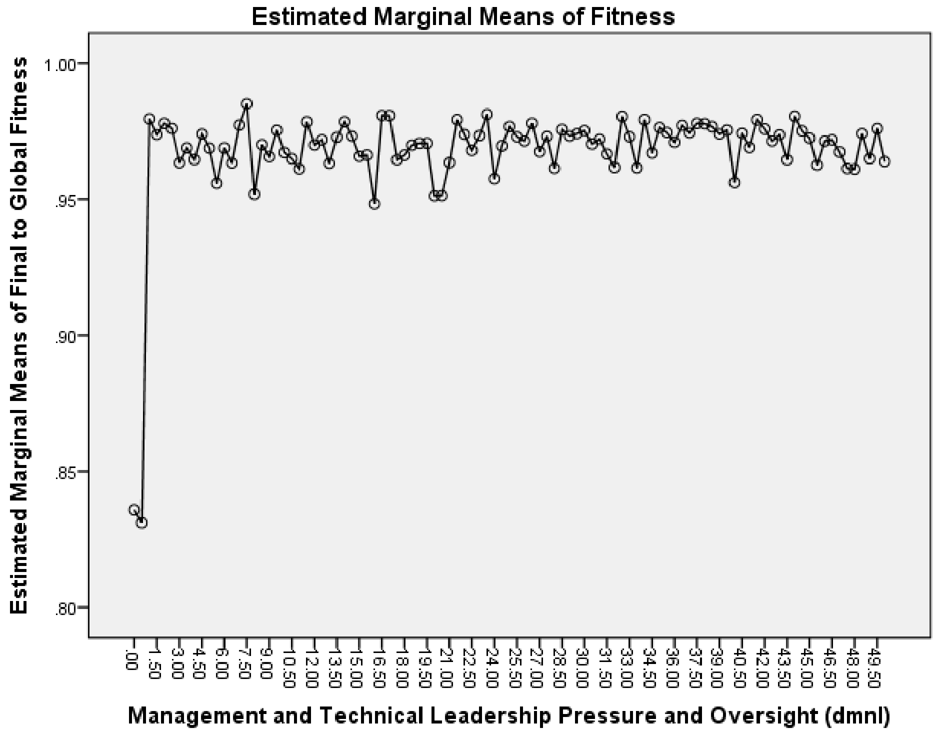


Figure Z.1 H8: Median Design Search-Time (steps) with Maximum-Downtime (steps)

Appendix AA: Hypothesis 9 Management Pressure



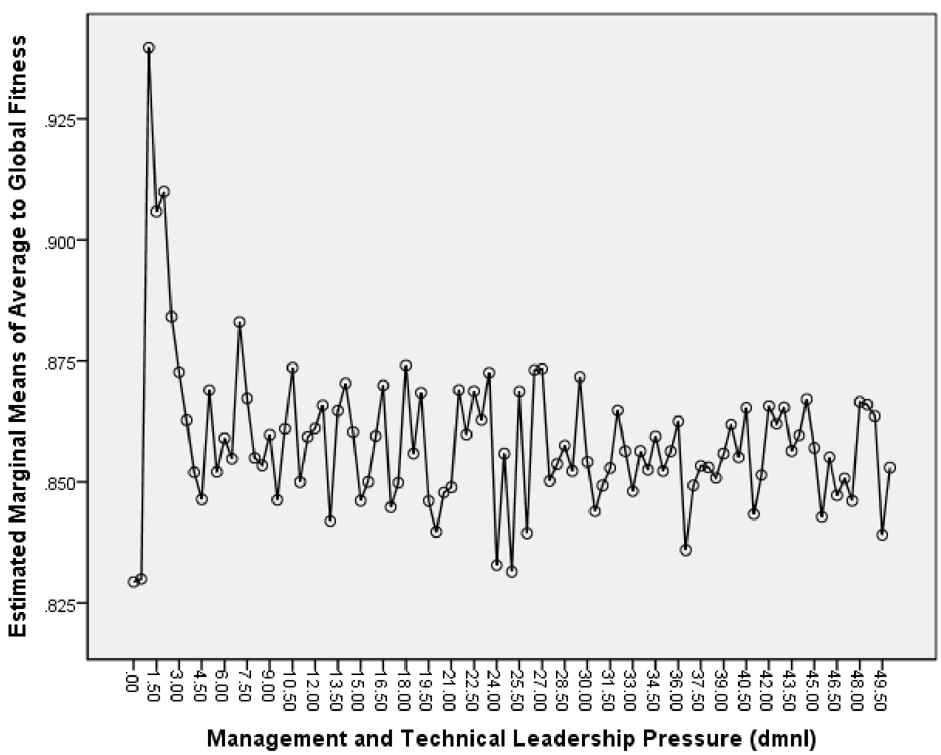


Figure AA.1 H9: Management Pressure and Fitness (Wide Range of Lambda)

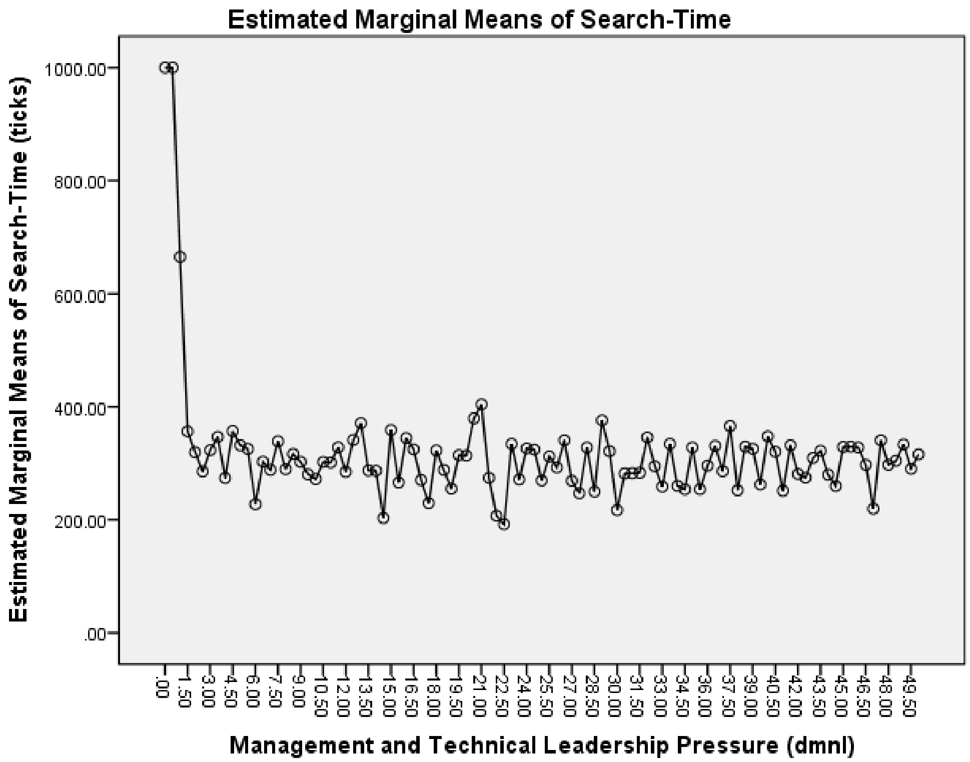


Figure AA.2 H9: Management Pressure and Search-Time (Wide Range of Lambda)

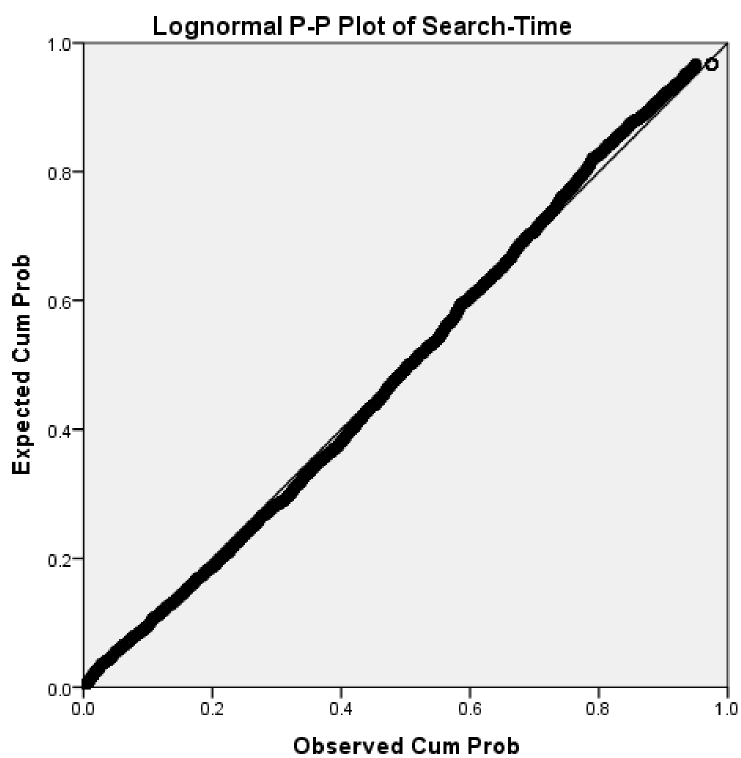


Figure AA.3 H9: Lognormal P-P Plot of Search-Time (Wide Range of Lambda)

Table AA.1 H9: Test of Between Subject Effect for Management Pressure (Wide Range of Lambda)

Source	Dep. Var. [h]	Type III Sum of Squares	df	Mean Square	F (100, 2424)	Sig.	Noncent. Param.	Obs. Power[g]
Corrected Model	f_t	1.051[a]	100	.011	6.980	.000	698.026	1.000
	$max f_t$	.075[b]	100	.001	1.071	.300	107.088	1.000
	$\overline{f_t}$	.595[c]	100	.006	2.465	.000	246.522	1.000
	C_f	.327[d]	100	.003	.926	.686	92.558	.999
	$\overline{C}$	.039[e]	100	.000	3.466	.000	346.586	1.000
	t_s	31107204.19[f]	100	311072.042	5.885	.000	588.498	1.000
Intercept	f_t	2364.140	1	2364.140	1569615.08	.000	1569615.08	1.000
	$max f_t$	2418.606	1	2418.606	3433078.21	.000	3433078.21	1.000
	$\overline{f_t}$	1859.932	1	1859.932	770615.226	.000	770615.226	1.000
	C_f	1767.839	1	1767.839	501144.692	.000	501144.692	1.000
	$\overline{C}$	1763.597	1	1763.597	15660626.7	.000	15660626.7	1.000
	t_s	255322200.25	1	255322200.3	4830.284	.000	4830.284	1.000
Mgmt. Pressure	f_t	1.051	100	.011	6.980	.000	698.026	1.000
	$max f_t$	.075	100	.001	1.071	.300	107.088	1.000
	$\overline{f_t}$	.595	100	.006	2.465	.000	246.522	1.000
	C_f	.327	100	.003	.926	.686	92.558	.999
	$\overline{C}$	.039	100	.000	3.466	.000	346.586	1.000
	t_s	31107204.192	100	311072.042	5.885	.000	588.498	1.000
Error	f_t	3.651	2424	.002				
	$max f_t$	1.708	2424	.001				
	$\overline{f_t}$	5.850	2424	.002				
	C_f	8.551	2424	.004				
	$\overline{C}$	.273	2424	.000				
	t_s	128129314.56	2424	52858.628				
Total	f_t	2368.842	2525					
	$max f_t$	2420.389	2525					
	$\overline{f_t}$	1866.378	2525					
	C_f	1776.717	2525					
	$\overline{C}$	1763.909	2525					
	t_s	414558719.00	2525					
Corrected Total	f_t	4.702	2524					
	$max f_t$	1.783	2524					
	$\overline{f_t}$	6.445	2524					
	t_s	8.877	2524					

a. R Squared = .224 (Adjusted R Squared = .192)

b. R Squared = .042 (Adjusted R Squared = .003)

c. R Squared = .092 (Adjusted R Squared = .055)

d. R Squared = .037 (Adjusted R Squared = -.003)

e. R Squared = .125 (Adjusted R Squared = .089)

f. R Squared = .195 (Adjusted R Squared = .162)

g. Computed using alpha = .05

h. Fitness measured relative to global max. fitness (f_m)

Table AA.2 H9: Correlations with Management Pressure (Wide Range of Lambda)

Correlations

			λ_u	t_s	f_t	$max(f_t)$	$\overline{f_t}$	C_f	$\overline{C}$
Spearman's Rho (ρ) [a]	λ_u	Correlation Coefficient	1.000	-.079**	.065**	.018	-.077**	.056**	.110**
		Sig. (2-tailed)	.	.000	.001	.372	.000	.005	.000
		N	2525	2525	2525	2525	2525	2525	2525
	t_s	Correlation Coefficient	-.079**	1.000	-.097**	.078**	-.296**	-.044*	.017
		Sig. (2-tailed)	.000	.	.000	.000	.000	.026	.384
		N	2525	2525	2525	2525	2525	2525	2525
	f_t	Correlation Coefficient	.065**	-.097**	1.000	.846**	.089**	.030	.026
		Sig. (2-tailed)	.001	.000	.	.000	.000	.130	.198
		N	2525	2525	2525	2525	2525	2525	2525
	$max(f_t)$	Correlation Coefficient	.018	.078**	.846**	1.000	.098**	.015	-.011
		Sig. (2-tailed)	.372	.000	.000	.	.000	.446	.595
		N	2525	2525	2525	2525	2525	2525	2525
	$\overline{f_t}$	Correlation Coefficient	-.077**	-.296**	.089**	.098**	1.000	.011	-.062**
		Sig. (2-tailed)	.000	.000	.000	.000	.	.590	.002
		N	2525	2525	2525	2525	2525	2525	2525
	C_f	Correlation Coefficient	.056**	-.044*	.030	.015	.011	1.000	.143**
		Sig. (2-tailed)	.005	.026	.130	.446	.590	.	.000
		N	2525	2525	2525	2525	2525	2525	2525
	$\overline{C}$	Correlation Coefficient	.110**	.017	.026	-.011	-.062**	.143**	1.000
		Sig. (2-tailed)	.000	.384	.198	.595	.002	.000	.
		N	2525	2525	2525	2525	2525	2525	2525

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).
a. Fitness variables measured relative to global maximum fitness (f_m)

Table AA.3 H9: Pearson Correlation

			λ_u	f_t	$\overline{f_t}$	t_s	C_f	$\overline{C}$
Pearson Correlation	λ_u (0 to 2.5)	Correlation Coefficient	1.000	.633**	.353**	-.835**	.128**	.600**
		Sig. (2-tailed)	.	.000	.000	.000	.004	.000
		N	510	510	510	510	510	510
	λ_u (0 to 50)	Correlation Coefficient	1.000	.120**	-.077**	-.126**	.049*	.122**
		Sig. (2-tailed)	.	.000	.000	.000	.014	.000
		N	2525	2525	2525	2525	2525	2525

a. Fitness measured relative to global max. fitness (f_m)
*. Correlation is significant at the 0.05 level (2-tailed).
**. Correlation is significant at the 0.01 level (2-tailed).

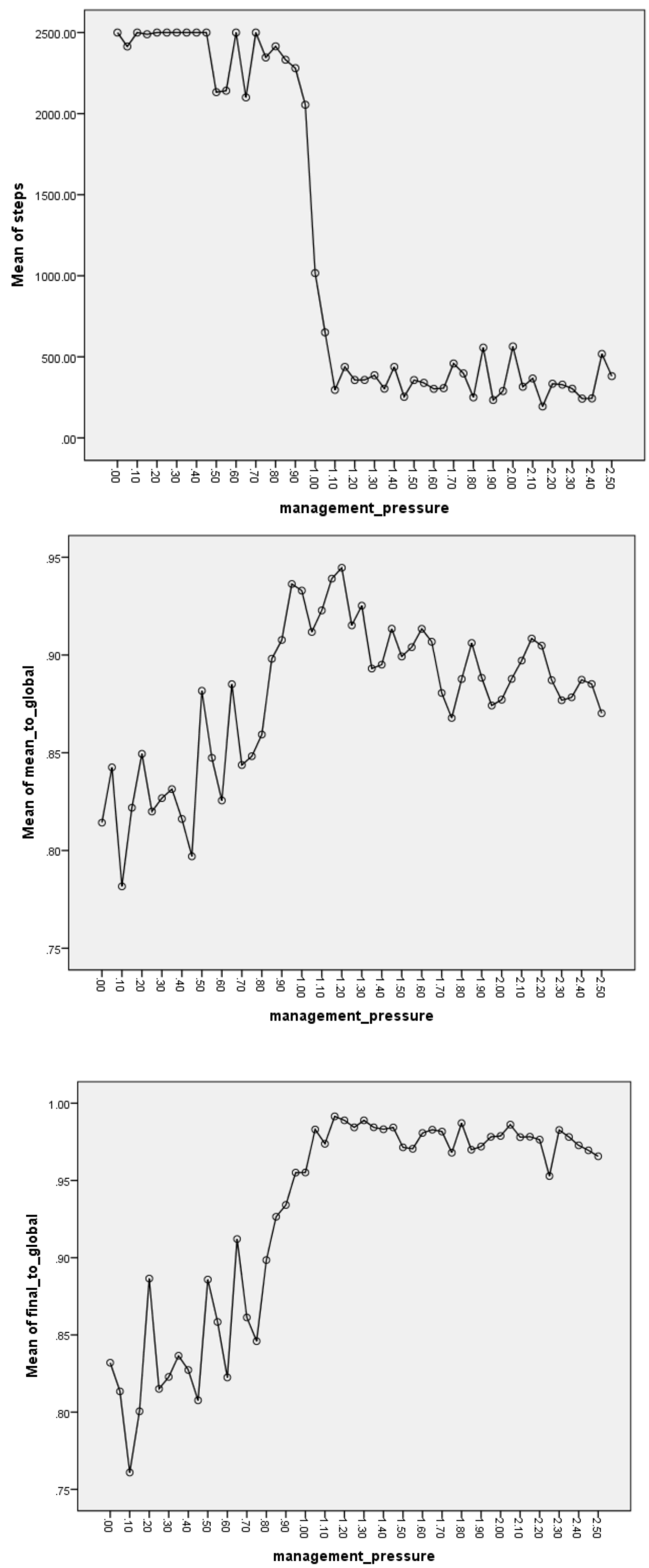


Figure AA.4 H9: Marginal Means of Performance (Phase Transition Range of Lambda)

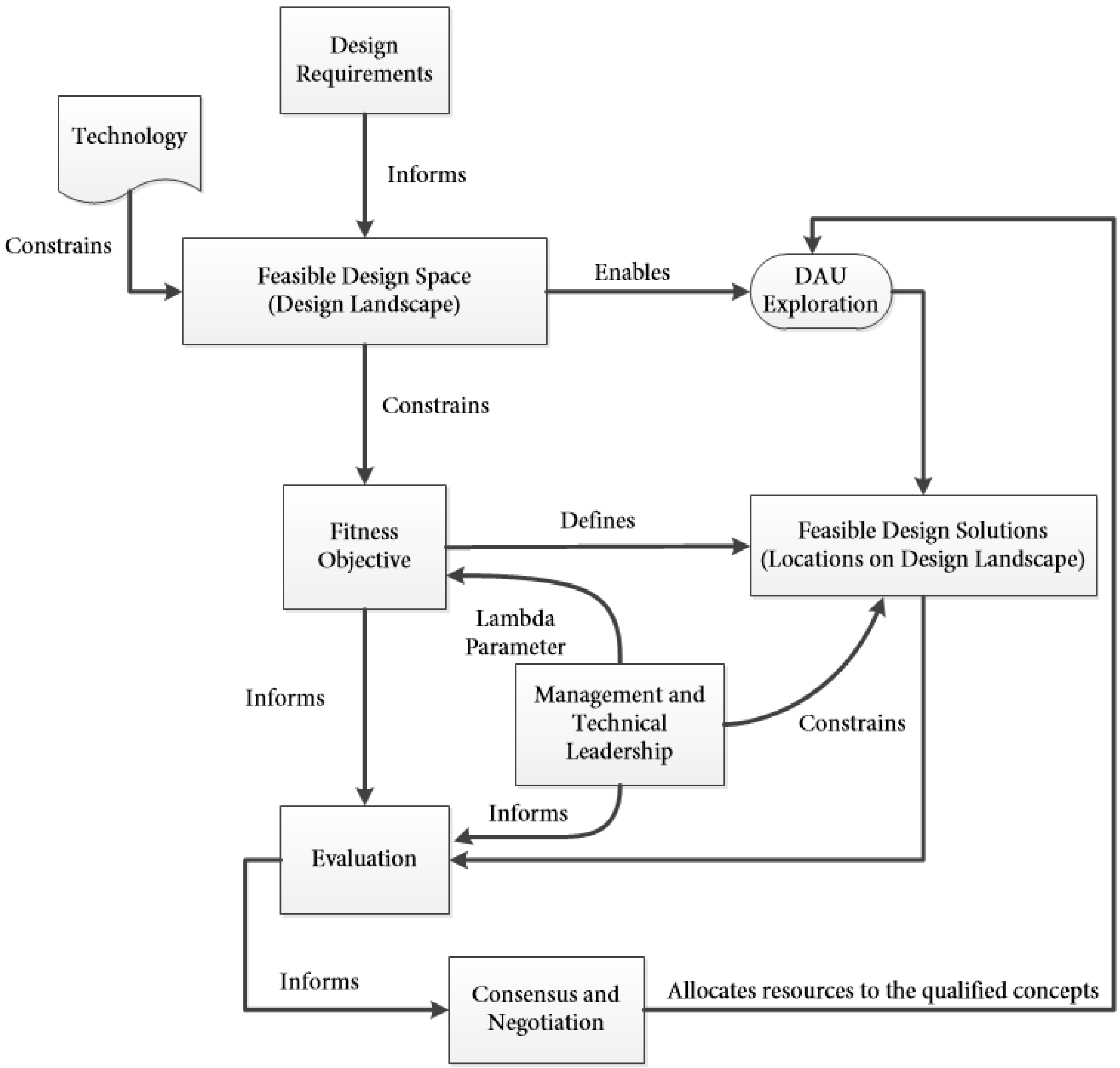


Figure AA.5 H9: Conceptual Functional Model for Management Pressure in the Simulations

Appendix AB: Hypothesis 10 Situational Management

Table AB.1 H10: Test of Between-Subject Effects for Consensus Strategy

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Noncent. Parameter	Observed Power[g]
Corrected Model	f_t	.052[a]	16	.003	2.208	.005	35.334	.983
	$max(f_t)$	.007[b]	16	.000	.798	.689	12.764	.557
	$\overline{f_t}$	.393[c]	16	.025	13.423	.000	214.764	1.000
	C_f	.071[e]	16	.004	1.843	.024	29.494	.952
	$\overline{C}$	.017[f]	16	.001	10.954	.000	175.266	1.000
	t_s	17338165.747[d]	16	1083635.359	15.039	.000	240.628	1.000
Intercept	f_t	278.892	1	278.892	189692.803	.000	189692.803	1.000
	$max(f_t)$	287.629	1	287.629	527836.740	.000	527836.740	1.000
	$\overline{f_t}$	235.295	1	235.295	128687.570	.000	128687.570	1.000
	C_f	208.621	1	208.621	86688.483	.000	86688.483	1.000
	$\overline{C}$	205.955	1	205.955	2102681.725	.000	2102681.725	1.000
	t_s	62790438.944	1	62790438.944	871.438	.000	871.438	1.000
mdt	f_t	.004	2	.002	1.300	.274	2.599	.281
	$max(f_t)$	.001	2	.001	1.107	.331	2.215	.245
	$\overline{f_t}$	.151	2	.075	41.269	.000	82.538	1.000
	C_f	.001	2	.000	.175	.840	.350	.077
	$\overline{C}$	.005	2	.003	27.995	.000	55.990	1.000
	t_s	2130197.618	2	1065098.809	14.782	.000	29.564	.999
$\lambda_{u\_initial}$	f_t	.003	3	.001	.698	.554	2.093	.198
	$max(f_t)$	.001	3	.000	.605	.612	1.816	.176
	$\overline{f_t}$	.002	3	.001	.310	.818	.931	.110
	C_f	.003	3	.001	.353	.787	1.058	.119
	$\overline{C}$	.000	3	.000	1.496	.215	4.489	.396
	t_s	59914.717	3	19971.572	.277	.842	.832	.103
Consensus Strategy Application	f_t	.031	1	.031	21.401	.000	21.401	.996
	$max(f_t)$	1.065E-005	1	1.065E-005	.020	.889	.020	.052
	$\overline{f_t}$	.164	1	.164	89.432	.000	89.432	1.000
	C_f	.049	1	.049	20.428	.000	20.428	.995
	$\overline{C}$	.008	1	.008	82.944	.000	82.944	1.000
	t_s	11821474.133	1	11821474.133	164.064	.000	164.064	1.000

Table AB.1 H10: Test of Between-Subject Effects for Consensus Strategy (Continued)

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Noncent. Parameter	Observed Power[g]
$mdt * \lambda_{u\_initial}$	f_t	.002	3	.001	.362	.781	1.085	.121
	$max(f_t)$	.001	3	.000	.589	.622	1.767	.173
	$\overline{f_t}$	.002	3	.001	.360	.782	1.079	.121
	C_f	.001	3	.000	.099	.961	.297	.068
	$\overline{C}$	.000	3	3.526E-005	.360	.782	1.080	.121
	t_s	388179.450	3	129393.150	1.796	.147	5.387	.468
mdt * strategy	f_t	.006	1	.006	4.057	.045	4.057	.520
	$max(f_t)$	.000	1	.000	.797	.373	.797	.145
	$\overline{f_t}$	.058	1	.058	31.691	.000	31.691	1.000
	C_f	.010	1	.010	4.297	.039	4.297	.543
	$\overline{C}$	.002	1	.002	20.767	.000	20.767	.995
	t_s	2403802.133	1	2403802.133	33.361	.000	33.361	1.000
$\lambda_{u\_initial}$ * strategy	f_t	.006	3	.002	1.329	.264	3.986	.355
	$max(f_t)$	.003	3	.001	1.672	.172	5.015	.438
	$\overline{f_t}$	.001	3	.000	.212	.888	.637	.090
	C_f	.000	3	.000	.058	.982	.173	.060
	$\overline{C}$	9.336E-005	3	3.112E-005	.318	.813	.953	.112
	t_s	126501.850	3	42167.283	.585	.625	1.756	.172
mdt * $\lambda_{u\_initial}$* strategy	f_t	.001	3	.000	.328	.805	.983	.114
	$max(f_t)$	.001	3	.000	.655	.580	1.964	.188
	$\overline{f_t}$	.010	3	.003	1.898	.129	5.693	.491
	C_f	.003	3	.001	.426	.734	1.279	.135
	$\overline{C}$	.000	3	5.821E-005	.594	.619	1.783	.174
	t_s	269427.317	3	89809.106	1.246	.292	3.739	.334
Error	f_t	.704	479	.001				
	$max(f_t)$	.261	479	.001				
	$\overline{f_t}$	.876	479	.002				
	C_f	1.153	479	.002				
	$\overline{C}$	.047	479	9.795E-005				
	t_s	34513790.671	479	72053.843				

Table AB.1 H10: Test of Between-Subject Effects for Consensus Strategy (Continued)

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Noncent. Parameter	Observed Power[g]
Total	f_t	465.343	496					
	$max(f_t)$	479.463	496					
	$\overline{f_t}$	392.410	496					
	C_f	347.042	496					
	$\overline{C}$	341.730	496					
	t_s	154100929.000	496					
Corrected Total	f_t	.756	495					
	$max(f_t)$	.268	495					
	$\overline{f_t}$	1.268	495					
	C_f	1.224	495					
	$\overline{C}$	.064	495					
	t_s	51851956.417	495					

a. R Squared = .069 (Adjusted R Squared = .038)
b. R Squared = .026 (Adjusted R Squared = -.007)
c. R Squared = .310 (Adjusted R Squared = .287)
d. R Squared = .334 (Adjusted R Squared = .312)
e. R Squared = .058 (Adjusted R Squared = .027)
f. R Squared = .268 (Adjusted R Squared = .243)
g. Computed using alpha = .05

Appendix AC: Hypothesis 11 Incremental Design

Table AC.1 H11: ANOVA of Data for Incremental Evolution Strategy [a]

Incremental Evolution Strategy		Sum of Squares	df	Mean Square	F	Sig.
t_s	Between Groups	2560.360	1	2560.360	.079	.779
	Within Groups	12958131.200	398	32558.119		
	Total	12960691.560	399			
f_t	Between Groups	.000	1	.000	.417	.519
	Within Groups	.391	398	.001		
	Total	.391	399			
$\overline{f_t}$	Between Groups	.000	1	.000	.000	.984
	Within Groups	.882	398	.002		
	Total	.882	399			
$max(f_t)$	Between Groups	.000	1	.000	.000	.993
	Within Groups	.252	398	.001		
	Total	.252	399			
C_f	Between Groups	.005	1	.005	1.877	.171
	Within Groups	1.120	398	.003		
	Total	1.125	399			
$\overline{C}$	Between Groups	.000	1	.000	.008	.929
	Within Groups	.051	398	.000		
	Total	.051	399			

Table AC.2 H11: Comparison of Correlations [a]

Consensus Management Strategy		t_s	f_t	$\overline{f_t}$	max(f)	C_f	$\overline{C}$	Final Path Length	Avg. Path Length
Spearman's Rho (ρ)	Correlation Coefficient	.024	-.042	.012	-.001	-.062	.009	.023	-.029
	Sig. (2-tailed)	.627	.403	.805	.989	.214	.853	.644	.558
	N	400	400	400	400	400	400	400	400
Pearson R Correlation	Correlation Coefficient	.014	-.032	.001	.000	-.069	.004	.047	-.021
	Sig. (2-tailed)	.779	.519	.984	.993	.171	.929	.347	.672
	N	400	400	400	400	400	400	400	400

**. Correlation is significant at the 0.01 level (2-tailed)
*. Correlation is significant at the 0.05 level (2-tailed)
a. Fitness variables measured relative to global maximum fitness (f_m)

Table AC.3 H11: Descriptive Statistics [a]

		N	Min.	Max.	Mean	Std. Deviation
Incremental Evolution Design Strategy On	t_s	200	46.00	1000.00	280.3400	183.38858
	f_t	200	.91	1.00	.9735	.03018
	$\overline{f_t}$	200	.76	.98	.8768	.04664
	max(f)	200	.91	1.00	.9818	.02502
	C_f	200	.68	.97	.8294	.05479
	$\overline{C}$	200	.79	.86	.8327	.01084
	Final Path Length	200	.00	21.85	.2401	2.01584
	Avg. Path Length	200	8.26	31.27	21.5940	4.71724
Incremental Evolution Design Strategy Off	t_s	200	43.00	1000.00	275.2800	177.43975
	f_t	200	.77	1.00	.9755	.03247
	$\overline{f_t}$	200	.76	.98	.8767	.04751
	max(f)	200	.91	1.00	.9818	.02526
	C_f	200	.70	1.00	.8367	.05124
	$\overline{C}$	200	.77	.86	.8326	.01172
	Final Path Length	200	.00	11.32	.0921	.94255
	Avg. Path Length	200	7.51	31.51	21.8003	5.00822
	Valid N (listwise)	200				

a. Fitness variables measured relative to global maximum fitness (f_m)

APPENDIX AD: HYPOTHESIS 12 COMPLEXITY AND THE DAU

Table AD.1 H12: Test of Between Subject Effects with Smoothness

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Noncent. Param.	Obs. Power[k]
Corrected Model when Consensus Not Required	t_s	1371513.328[a]	5	274302.666	37.824	.000	189.120	1.000
	f_t	.001[b]	5	.000	.529	.754	2.646	.197
	$\max(f)$	.001[c]	5	.000	.532	.752	2.662	.198
	$\overline{f_t}$	.245[d]	5	.049	21.991	.000	109.953	1.000
	C_f	.102[e]	5	.020	7.531	.000	37.654	.999
	$\max(C)$	.000[f]	5	.000	.	.	.	.
	$\overline{C}$	.065[g]	5	.013	12.088	.000	60.438	1.000
	Final Path L	3671.221[h]	5	734.244	14.337	.000	71.683	1.000
	Max Path L	50.119[i]	5	10.024	.457	.808	2.284	.174
	Mean Path L	970.721[j]	5	194.144	6.114	.000	30.569	.996
Intercept when Consensus Not Required	t_s	1993306.482	1	1993306.482	274.860	.000	274.860	1.000
	f_t	519.554	1	519.554	1119833.012	.000	1119833.012	1.000
	$\max(f)$	519.666	1	519.666	1146898.653	.000	1146898.653	1.000
	$\overline{f_t}$	340.467	1	340.467	153028.396	.000	153028.396	1.000
	C_f	397.988	1	397.988	147527.146	.000	147527.146	1.000
	$\max(C)$	600.000	1	600.000	.	.	.	.
	$\overline{C}$	415.663	1	415.663	387595.733	.000	387595.733	1.000
	Final Path L	413778.875	1	413778.875	8079.357	.000	8079.357	1.000
	Max Path L	961703.329	1	961703.329	43821.859	.000	43821.859	1.000
	Mean Path L	557962.408	1	557962.408	17570.621	.000	17570.621	1.000
Smoothness when Conesus Not Required	t_s	1371513.328	5	274302.666	37.824	.000	189.120	1.000
	f_t	.001	5	.000	.529	.754	2.646	.197
	$\max(f)$	.001	5	.000	.532	.752	2.662	.198
	$\overline{f_t}$	.245	5	.049	21.991	.000	109.953	1.000
	C_f	.102	5	.020	7.531	.000	37.654	.999
	$\max(C)$	.000	5	.000	.	.	.	.
	$\overline{C}$	.065	5	.013	12.088	.000	60.438	1.000
	Final Path L	3671.221	5	734.244	14.337	.000	71.683	1.000
	Max Path L	50.119	5	10.024	.457	.808	2.284	.174
	Mean Path L	970.721	5	194.144	6.114	.000	30.569	.996

Table AD.1 H12: Test of Between Subject Effects with Smoothness (Continued)

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Noncent. Param.	Obs. Power[k]
Error when Consensus Not Required	t_s	4307729.190	594	7252.069				
	f_t	.276	594	.000				
	$\max(f)$	.269	594	.000				
	$\overline{f_t}$	1.322	594	.002				
	C_f	1.602	594	.003				
	$\max(C)$	.000	594	.000				
	$\overline{C}$	.637	594	.001				
	Final Path L	30421.312	594	51.214				
	Max Path L	13035.772	594	21.946				
	Mean Path L	18862.718	594	31.755				
Total when Consensus Not Required	t_s	7672549.000	600					
	f_t	519.831	600					
	$\max(f)$	519.937	600					
	$\overline{f_t}$	342.033	600					
	C_f	399.692	600					
	$\max(C)$	600.000	600					
	$\overline{C}$	416.365	600					
	Final Path L	447871.408	600					
	Max Path L	974789.220	600					
	Mean Path L	577795.847	600					
Corrected Total when Consensus Not Required	t_s	5679242.518	599					
	f_t	.277	599					
	$\max(f)$	.270	599					
	$\overline{f_t}$	1.566	599					
	C_f	1.704	599					
	$\max(C)$	.000	599					
	$\overline{C}$	.702	599					
	Final Path L	34092.533	599					
	Max Path L	13085.891	599					
	Mean Path L	19833.438	599					

Table AD.1 H12: Test of Between Subject Effects with Smoothness (Continued)

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Noncent. Param.	Obs. Power[k]
Corrected Model when Consensus is Required	t_s	7237669.153[l]	5	1447533.83	37.966	.000	189.830	1.000
	f_t	.145[m]	5	.029	23.158	.000	115.791	1.000
	$\max(f)$	.107[n]	5	.021	46.342	.000	231.709	1.000
	$\overline{f_t}$	.267[o]	5	.053	27.088	.000	135.439	1.000
	C_f	.010[p]	5	.002	.682	.637	3.409	.248
	$\max(C)$	.000[f]	5	.000	.	.	.	.
	$\overline{C}$	.016[q]	5	.003	15.621	.000	78.106	1.000
	Final Path L	17.972[r]	5	3.594	.450	.813	2.250	.171
	Max Path L	193.093[s]	5	38.619	2.168	.056	10.841	.714
	Mean Path L	2797.016[t]	5	559.403	21.917	.000	109.587	1.000
Intercept when Consensus is Required	t_s	34596489.627	1	34596489.6	907.397	.000	907.397	1.000
	f_t	573.901	1	573.901	458753.176	.000	458753.176	1.000
	$\max(f)$	582.120	1	582.120	1265399.605	.000	1265399.605	1.000
	$\overline{f_t}$	468.760	1	468.760	238169.648	.000	238169.648	1.000
	C_f	421.409	1	421.409	137900.323	.000	137900.323	1.000
	$\max(C)$	600.000	1	600.000	.	.	.	.
	$\overline{C}$	412.616	1	412.616	2030484.701	.000	2030484.701	1.000
	Final Path L	98.716	1	98.716	12.356	.000	12.356	.939
	Max Path L	982418.369	1	982418.369	55155.442	.000	55155.442	1.000
	Mean Path L	206870.416	1	206870.416	8105.192	.000	8105.192	1.000
Smoothness when Consensus is Required	t_s	7237669.153	5	1447533.83	37.966	.000	189.830	1.000
	f_t	.145	5	.029	23.158	.000	115.791	1.000
	$\max(f)$	.107	5	.021	46.342	.000	231.709	1.000
	$\overline{f_t}$	.267	5	.053	27.088	.000	135.439	1.000
	C_f	.010	5	.002	.682	.637	3.409	.248
	$\max(C)$	.000	5	.000	.	.	.	.
	$\overline{C}$	.016	5	.003	15.621	.000	78.106	1.000
	Final Path L	17.972	5	3.594	.450	.813	2.250	.171
	Max Path L	193.093	5	38.619	2.168	.056	10.841	.714
	Mean Path L	2797.016	5	559.403	21.917	.000	109.587	1.000

Table AD.1 H12: Test of Between Subject Effects with Smoothness (Continued)

Error when Consensus is Required	t_s	22647543.220	594	38127.177
	f_t	.743	594	.001
	$\max(f)$	.273	594	.000
	$\overline{f_t}$	1.169	594	.002
	C_f	1.815	594	.003
	$\max(C)$	.000	594	.000
	$\overline{C}$	.121	594	.000
	Final Path L	4745.642	594	7.989
	Max Path L	10580.216	594	17.812
	Mean Path L	15160.780	594	25.523
Total when Consensus is Required	t_s	64481702.000	600	
	f_t	574.789	600	
	$\max(f)$	582.500	600	
	$\overline{f_t}$	470.196	600	
	C_f	423.235	600	
	$\max(C)$	600.000	600	
	$\overline{C}$	412.752	600	
	Final Path L	4862.330	600	
	Max Path L	993191.678	600	
	Mean Path L	224828.212	600	
Corrected Total when Consensus is Required	t_s	29885212.373	599	
	f_t	.888	599	
	$\max(f)$	.380	599	
	$\overline{f_t}$	1.436	599	
	C_f	1.826	599	
	$\max(C)$	.000	599	
	$\overline{C}$	.137	599	
	Final Path L	4763.614	599	
	Max Path L	10773.310	599	
	Mean Path L	17957.796	599	

a. R Squared = .241 (Adjusted R Squared = .235)
b. R Squared = .004 (Adjusted R Squared = -.004)
c. R Squared = .004 (Adjusted R Squared = -.004)
d. R Squared = .156 (Adjusted R Squared = .149)
e. R Squared = .060 (Adjusted R Squared = .052)
f. R Squared = . (Adjusted R Squared = .) Const.
g. R Squared = .092 (Adjusted R Squared = .085)
h. R Squared = .108 (Adjusted R Squared = .100)
i. R Squared = .004 (Adjusted R Squared = -.005)
j. R Squared = .049 (Adjusted R Squared = .041)
k. Computed using alpha = .05
l. R Squared = .242 (Adjusted R Squared = .236)
m. R Squared = .163 (Adjusted R Squared = .156)
n. R Squared = .281 (Adjusted R Squared = .275)
o. R Squared = .186 (Adjusted R Squared = .179)
p. R Squared = .006 (Adjusted R Squared = -.003)
q. R Squared = .116 (Adjusted R Squared = .109)
r. R Squared = .004 (Adjusted R Squared = -.005)
s. R Squared = .018 (Adjusted R Squared = .010)
t. R Squared = .156 (Adjusted R Squared = .149)

Table AD.2 H12: Descriptive Statistics with Smoothness when No Consensus

Descriptive Statistics

		S	Mean	Std. Deviation	N
No Consensus Required	t_s	.00	159.0000	158.60745	100
		20.00	56.9900	66.41049	100
		40.00	52.0900	96.02852	100
		60.00	34.6300	47.33049	100
		80.00	33.3300	49.58720	100
		100.00	9.7900	5.01975	100
		Total	57.6383	97.37149	600
	f_t	.00	.9298	.01911	100
		20.00	.9322	.01874	100
		40.00	.9314	.02007	100
		60.00	.9292	.02050	100
		80.00	.9322	.02173	100
		100.00	.9286	.02779	100
		Total	.9306	.02150	600
	$\overline{f_t}$	.00	.7819	.03297	100
		20.00	.7666	.03953	100
		40.00	.7454	.04706	100
		60.00	.7556	.04310	100
		80.00	.7541	.04430	100
		100.00	.7161	.06830	100
		Total	.7533	.05113	600

Table AD.3 H12: Descriptive Statistics with Smoothness with Requisite Consensus

Descriptive Statistics

		S	Mean	Std. Deviation	N
Consensus Required	t_s	.00	398.7000	248.64727	100
		20.00	323.1200	240.76487	100
		40.00	235.3800	179.81976	100
		60.00	228.4900	222.28771	100
		80.00	213.6500	164.64154	100
		100.00	41.4200	10.77331	100
		Total	240.1267	223.36481	600
	f_t	.00	.9504	.03325	100
		20.00	.9676	.05381	100
		40.00	.9841	.03685	100
		60.00	.9808	.03806	100
		80.00	.9852	.02643	100
		100.00	1.0000	.00005	100
		Total	.9780	.03850	600
	$\overline{f_t}$	.00	.8406	.04056	100
		20.00	.8753	.04551	100
		40.00	.8932	.04130	100
		60.00	.8966	.04259	100
		80.00	.9026	.04460	100
		100.00	.8950	.05084	100
		Total	.8839	.04896	600

APPENDIX AE: HYPOTHESIS 13 STRUCTURING DESIGN

Table AE.1 Wilcoxon Signed Ranks Test (No Consensus)

Ranks

				N	Mean Rank	Sum of Ranks
Consensus Off	N = 3, K=1 Minus N=5, K=0	f_t	Negative Ranks	47[a]	43.91	2064.00
			Positive Ranks	52[b]	55.50	2886.00
			Ties	1[c]		
			Total	100		
		$\overline{f_t}$	Negative Ranks	100[d]	50.50	5050.00
			Positive Ranks	0[e]	.00	.00
			Ties	0[f]		
			Total	100		
		t_s	Negative Ranks	39[g]	46.33	1807.00
			Positive Ranks	54[h]	47.48	2564.00
			Ties	7[i]		
			Total	100		
	N = 3, K=2 Minus N=9, K=0	f_t	Negative Ranks	54[j]	40.06	2163.00
			Positive Ranks	14[k]	13.07	183.00
			Ties	32[l]		
			Total	100		
		$\overline{f_t}$	Negative Ranks	83[m]	58.20	4831.00
			Positive Ranks	17[n]	12.88	219.00
			Ties	0[o]		
			Total	100		
		t_s	Negative Ranks	70[p]	40.78	2854.50
			Positive Ranks	30[q]	73.18	2195.50
			Ties	0[r]		
			Total	100		

a. ff_3_1 < ff_5_0
b. ff_3_1 > ff_5_0
c. ff_3_1 = ff_5_0
d. mf_3_1 < mf_5_0
e. mf_3_1 > mf_5_0
f. mf_3_1 = mf_5_0
g. steps_3_1 < steps_5_0
h. steps_3_1 > steps_5_0
i. steps_3_1 = steps_5_0
j. ff_3_2 < ff_9_0
k. ff_3_2 > ff_9_0
l. ff_3_2 = ff_9_0
m. mf_3_2 < mf_9_0
n. mf_3_2 > mf_9_0
o. mf_3_2 = mf_9_0
p. steps_3_2 < steps_9_0
q. steps_3_2 > steps_9_0
r. steps_3_2 = steps_9_0

** ff = f_t , mf = $\overline{f_t}$, steps = t_s , _N_K

Table AE.2 Wilcoxon Signed Ranks Test (With Consensus)

Ranks

				N	Mean Rank	Sum of Ranks
Consensus On	N = 3, K=1 Minus N=5, K=0	f_t	Negative Ranks	49[a]	39.73	1947.00
			Positive Ranks	17[b]	15.53	264.00
			Ties	34[c]		
			Total	100		
		$\overline{f_t}$	Negative Ranks	56[d]	63.89	3578.00
			Positive Ranks	44[e]	33.45	1472.00
			Ties	0[f]		
			Total	100		
		t_s	Negative Ranks	43[g]	28.84	1240.00
			Positive Ranks	57[h]	66.84	3810.00
			Ties	0[i]		
			Total	100		
	N = 3, K=2 Minus N=9, K=0	f_t	Negative Ranks	30[j]	54.20	1626.00
			Positive Ranks	70[k]	48.91	3424.00
			Ties	0[l]		
			Total	100		
		$\overline{f_t}$	Negative Ranks	100[m]	50.50	5050.00
			Positive Ranks	0[n]	.00	.00
			Ties	0[o]		
			Total	100		
		t_s	Negative Ranks	27[p]	36.31	980.50
			Positive Ranks	67[q]	52.01	3484.50
			Ties	6[r]		
			Total	100		

a. ff_3_1 < ff_5_0
b. ff_3_1 > ff_5_0
c. ff_3_1 = ff_5_0
d. mf_3_1 < mf_5_0
e. mf_3_1 > mf_5_0
f. mf_3_1 = mf_5_0
g. steps_3_1 < steps_5_0
h. steps_3_1 > steps_5_0
i. steps_3_1 = steps_5_0
j. ff_3_2 < ff_9_0
k. ff_3_2 > ff_9_0
l. ff_3_2 = ff_9_0
m. mf_3_2 < mf_9_0
n. mf_3_2 > mf_9_0
o. mf_3_2 = mf_9_0
p. steps_3_2 < steps_9_0
q. steps_3_2 > steps_9_0
r. steps_3_2 = steps_9_0
** ff = f_t , mf = $\overline{f_t}$, steps = t_s , _N_K

Table AE.3 Descriptive Statistics for Different Design Approaches

Descriptive Statistics

			N	Minimum	Maximum	Mean	Std. Deviation
Consensus Off	N=5, K=0	f_t	100	.89	1.00	.9329	.02953
	N=3, K=1	f_t	100	.86	1.00	.9397	.04222
	N=5, K=0	$\overline{f_t}$	100	.45	.93	.6998	.06738
	N=3, K=1	$\overline{f_t}$	100	.23	.58	.3947	.07849
	N=5, K=0	t_s	100	.00	26.00	10.5000	5.08613
	N=3, K=1	t_s	100	5.00	19.00	11.1100	2.82805
	N=3, K=2	f_t	100	.94	1.00	.9951	.01030
	N=9, K=0	f_t	100	.98	1.00	.9998	.00191
	N=3, K=2	$\overline{f_t}$	100	.08	.99	.4675	.30061
	N=9, K=0	$\overline{f_t}$	100	.82	.97	.9027	.03106
	N=3, K=2	t_s	100	6.00	462.00	62.4400	88.61383
	N=9, K=0	t_s	100	21.00	279.00	46.6900	33.35899
	Valid N (listwise)		100				
Consensus On	N=5, K=0	f_t	100	.94	1.00	.9992	.00650
	N=3, K=1	f_t	100	.99	1.00	.9986	.00214
	N=5, K=0	$\overline{f_t}$	100	.73	.98	.8870	.04124
	N=3, K=1	$\overline{f_t}$	100	.34	.98	.7968	.17044
	N=5, K=0	t_s	100	22.00	452.00	43.8900	43.17404
	N=3, K=1	t_s	100	8.00	316.00	84.3900	75.07100
	N=3, K=2	f_t	100	.73	1.00	.9539	.06304
	N=9, K=0	f_t	100	.89	1.00	.9291	.02850
	N=3, K=2	$\overline{f_t}$	100	.04	.48	.2434	.09354
	N=9, K=0	$\overline{f_t}$	100	.49	.83	.7134	.06955
	N=3, K=2	t_s	100	5.00	60.00	15.3700	8.73361
	N=9, K=0	t_s	100	1.00	20.00	9.9300	3.97023
	Valid N (listwise)		100				

Table AE.4 ANOVA Tests of Between-Subject Effects (No Consensus)

Tests of Between-Subjects Effects

	Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Noncent. Parameter	Obs. Power[d]
Consensus Off	Corrected Model	f_t	.052[a]	8	.007	5.184	.000	41.474	.999
		$\overline{f_t}$	22.297[b]	8	2.787	559.706	.000	4477.649	1.000
		t_s	81486.440[c]	8	10185.805	19.046	.000	152.371	1.000
	Intercept	f_t	795.641	1	795.641	633209.793	.000	633209.793	1.000
		$\overline{f_t}$	312.192	1	312.192	62694.654	.000	62694.654	1.000
		t_s	350108.890	1	350108.890	654.666	.000	654.666	1.000
	N	f_t	.010	2	.005	4.035	.018	8.071	.720
		$\overline{f_t}$	10.870	2	5.435	1091.511	.000	2183.022	1.000
		t_s	25297.447	2	12648.723	23.652	.000	47.304	1.000
	K	f_t	.029	2	.014	11.364	.000	22.729	.993
		$\overline{f_t}$	6.213	2	3.107	623.878	.000	1247.757	1.000
		t_s	42033.087	2	21016.543	39.299	.000	78.597	1.000
	N * K	f_t	.013	4	.003	2.669	.031	10.675	.745
		$\overline{f_t}$	5.213	4	1.303	261.718	.000	1046.870	1.000
		t_s	14155.907	4	3538.977	6.618	.000	26.470	.992
	Error	f_t	1.120	891	.001				
		$\overline{f_t}$	4.437	891	.005				
		t_s	476497.670	891	534.790				
	Total	f_t	796.813	900					
		$\overline{f_t}$	338.925	900					
		t_s	908093.000	900					
	Corrected Total	f_t	1.172	899					
		$\overline{f_t}$	26.734	899					
		t_s	557984.110	899					

a. R Squared = .044 (Adjusted R Squared = .036)

b. R Squared = .834 (Adjusted R Squared = .833)

c. R Squared = .146 (Adjusted R Squared = .138)

d. Computed using alpha = .05

Table AE.5 ANOVA Tests of Between-Subject Effects (With Consensus)

Tests of Between-Subjects Effects

	Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Noncent. Parameter	Obs. Power[d]
Consensus On	Corrected Model	f_t	.010 [a]	8	.001	8.190	.000	65.519	1.000
		$\overline{f_t}$	15.265 [b]	8	1.908	121.549	.000	972.391	1.000
		t_s	4462886.389 [c]	8	557860.799	45.560	.000	364.482	1.000
	Intercept	f_t	892.982	1	892.982	5913636.881	.000	5913636.881	1.000
		$\overline{f_t}$	613.800	1	613.800	39099.343	.000	39099.343	1.000
		t_s	12693306.321	1	12693306.321	1036.658	.000	1036.658	1.000
	N	f_t	.002	2	.001	5.109	.006	10.217	.823
		$\overline{f_t}$	4.998	2	2.499	159.187	.000	318.375	1.000
		t_s	1372131.976	2	686065.988	56.031	.000	112.062	1.000
	K	f_t	.006	2	.003	20.365	.000	40.731	1.000
		$\overline{f_t}$	4.361	2	2.181	138.903	.000	277.805	1.000
		t_s	2276167.636	2	1138083.818	92.947	.000	185.894	1.000
	N * K	f_t	.002	4	.001	3.643	.006	14.571	.879
		$\overline{f_t}$	5.906	4	1.476	94.053	.000	376.211	1.000
		t_s	814586.778	4	203646.694	16.632	.000	66.527	1.000
	Error	f_t	.135	891	.000				
		$\overline{f_t}$	13.987	891	.016				
		t_s	10909804.290	891	12244.449				
	Total	f_t	893.127	900					
		$\overline{f_t}$	643.052	900					
		t_s	28065997.000	900					
	Corrected Total	f_t	.144	899					
		$\overline{f_t}$	29.252	899					
		t_s	15372690.679	899					

a. R Squared = .068 (Adjusted R Squared = .060)
b. R Squared = .522 (Adjusted R Squared = .518)
c. R Squared = .290 (Adjusted R Squared = .284)
d. Computed using alpha = .05

APPENDIX AF: SYSTEM DYNAMIC REPRESENTATION

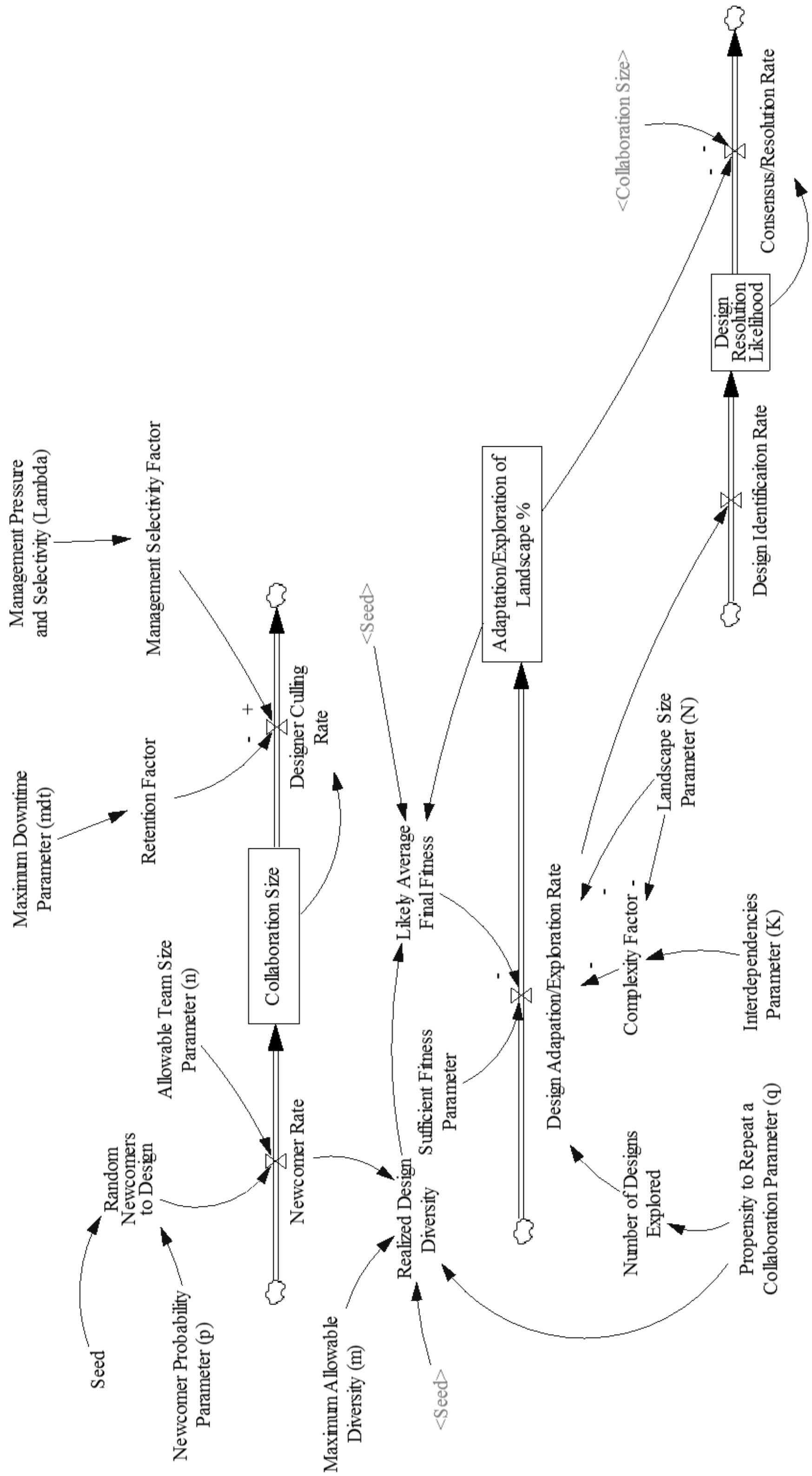


Figure AF.1 Systems Dynamics Model for C²D Simulations

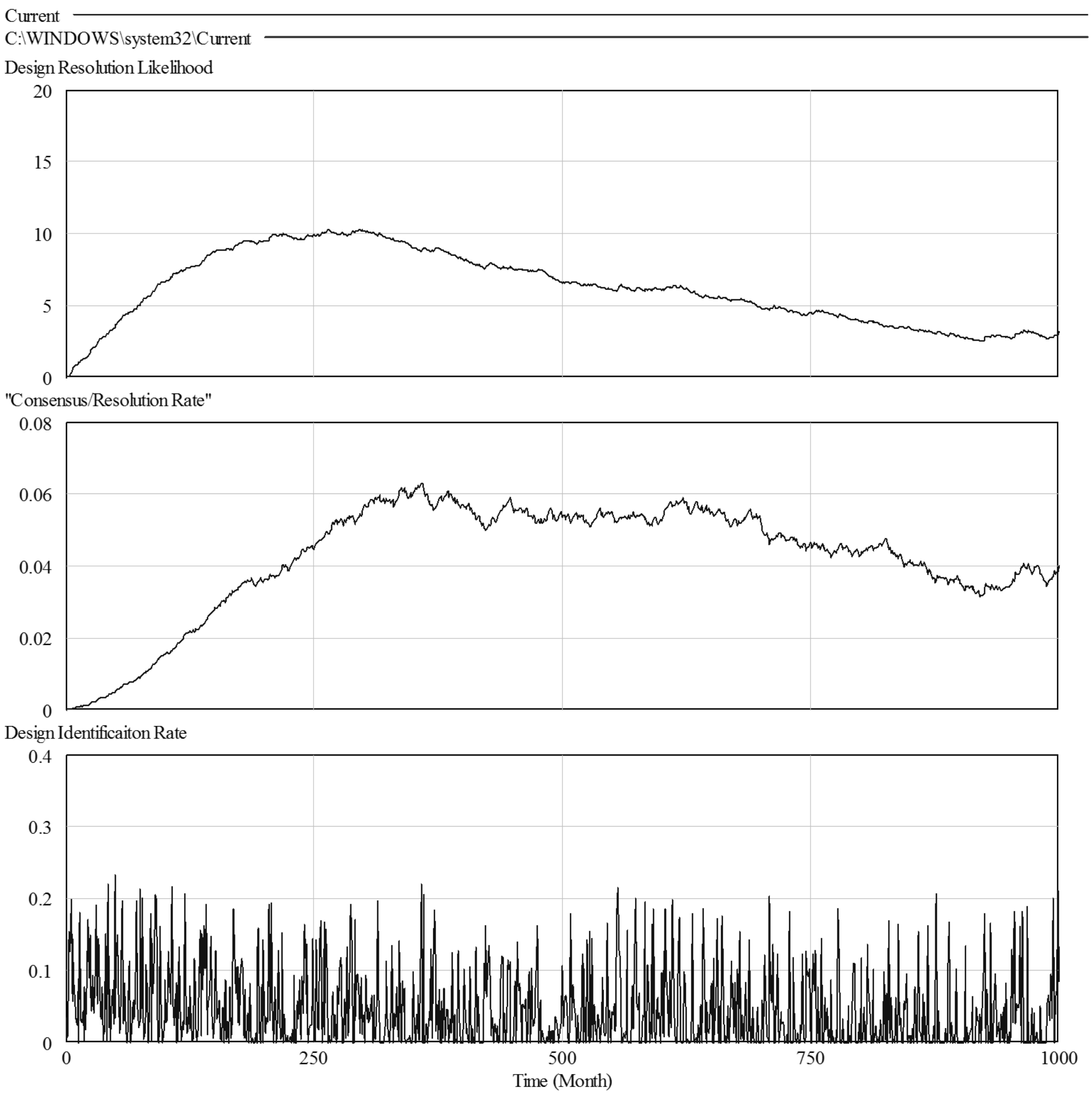


Figure AF.2 Sample Output for N=5, K=4

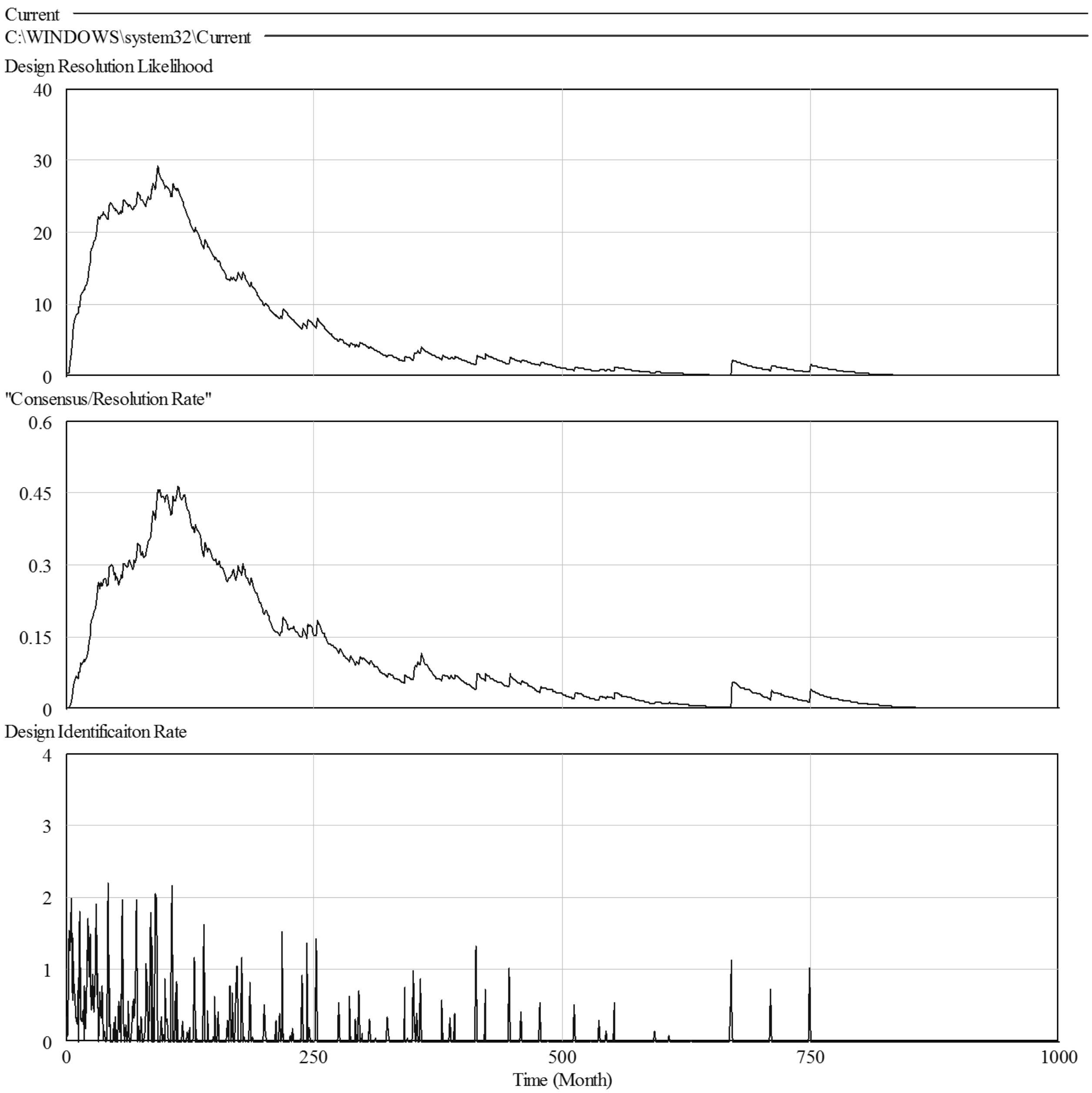


Figure AF.3 Sample Output for N=5, K=0