Modeling and Measuring Affordability as Fitness

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Abstract

Affordability of products and services is an economic benefit that should accrue to consumers, whether they are corporations, government agencies or individuals. This concept of affordability goes beyond conventional wisdom that considers affordability as the ability to pay the price of a product or service. This dissertation defines and explores a broader concept of affordability – one of fitness to perform at the level of quality required by the consumer, to perform at that level whenever the product or service is used, and to do so with minimum consumption of resources. This concept of affordability is applied to technological systems by using the complexity sciences concept of fitness as the metaphor for technological systems' fitness. During a system design evolution, the specific design outcome is determined by that set of design search paths followed – it is path dependent. Dynamic mechanisms create, dictate and maintain path dependence. Initial conditions define the start and direction of a path. During subsequent design steps, positive feedback influences the designer to continue on that path. This dissertation describes underlying mechanisms that create, dictate and maintain path dependence; discusses the effects of path dependence on system design and system affordability; models these effects using system dynamics modeling; and suggests actions to address its effects. This dissertation also addresses several types of fitness landscapes, and suggests that the Data Envelopment Analysis (DEA) solution space is a form of fitness landscape suitable for evaluating the efficiency, and thus the fitness, of research and development (R&D) projects. It describes the use of DEA to evaluate and select Department of Defense (D0D) R&D projects as a new application of DEA.

To my wife, Nancy

Acknowledgements

Six years ago, after much trepidation but with guidance and motivation from my advisor and now committee chairman, Dr. Konstantinos Triantis, I embarked upon a journey into what was largely the educational unknown to pursue a Ph.D. in Industrial and Systems Engineering. My initial exposure to research at Virginia Tech occurred in the early 2000s as a result of the university's participation in the Office of Naval Research (ONR) Affordability Management and Prediction program. My involvement as an ONR technical representative to the Virginia Tech research team introduced me to Virginia Tech, Dr. Triantis, and system dynamics. After several years, Dr. Triantis convinced me to begin what has been an interesting, sometimes exciting, other times frustrating, but in the end a rewarding adventure. Dr. Triantis has exceeded all expectations as a professor, mentor, advisor and true friend, guiding and encouraging me through the academic maze, over and around obstacles and pitfalls, and on to this point in my professional, academic and personal life where I stand on the brink of a new, significant accomplishment. There is no doubt that, without his unwavering support, I would never have reached this sometimes-elusive goal.

The other members of my committee have also had a lasting, positive impact on my academic pursuit. Dr. Brian Kleiner was my first Virginia Tech professor and introduced me to the Virginia Tech academic classroom world and to macroergonomics. Dr. Kleiner was very interested in my concepts and ideas regarding affordability, reinforcing my contention that affordability was a fertile area to explore and convincing me that it could be a valuable tool in the field of macroergonomics as well as in the broader set of industrial and systems engineering disciplines. I was delighted and honored that Dr. Kleiner agreed to serve as a member of my committee. Dr. Hazhir Rahmandad is an outstanding professor who imparted knowledge, comprehension and hopefully some skill in the application of system dynamics thinking and modeling to industrial and systems engineering problems, and particularly to the analysis and prediction of affordability-related dynamic relationships. He challenged me to not only master the fundamentals and

the more sophisticated details of system dynamics programming, but also the clear communication of the logic and structure of causal relations and model equations.

My association with Dr. David Moran has spanned nearly twenty years, during which he instituted Affordability Science at ONR and launched me on a search for affordability concepts, principles, disciplines and answers to many of the questions addressed in this dissertation. Without his perception, energy, motivation, sharing of ideas, willingness to explore the complexity sciences, and true belief in affordability as a crucial element of product and service development, it is unlikely that I would have continued to develop any of the affordability concepts and principles presented in this dissertation. Ms. Katherine Drew took over the Affordability Science program from Dr. Moran and provided me the opportunity to continue on the research trajectory that I started in 1995. She encouraged me to carry on the pursuit of affordability as fitness and actively supported research and application of complexity sciences concepts and techniques in the Affordability Measurement and Prediction Program that she instituted and managed. I am extremely fortunate that both Dr. Moran and Ms. Drew agreed to serve on my committee, where their experience and wisdom has been most important and their support and encouragement outstanding.

Mr. Daniel Dunmire, the Director of Corrosion Policy and Oversight and a Ph.D. candidate in Public Administration and Policy at Virginia Tech, is a client and close friend who recognized the value of modern engineering techniques and embraced DEA as an evaluation tool for the Corrosion Prevention and Control program. His deep interest in industrial and systems engineering capabilities, his encouragement, and our friendly competition in our mutual pursuit of a Ph.D. from Virginia Tech has been inspirational and very important. Others who have inspired and encouraged me are Dr. Bruce Bueno de Mesquita of the Hoover Institute at Stanford University, Dr. Airan Perez of the Office of Naval Research, and Dr. Dimitri Mavris of Georgia Tech.

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1. Introduction

1.1 Affordability in Context

Conventional wisdom and usage regards affordability as a cost characteristic of a product or service that determines a purchaser’s ability to pay its price. The term frequently appears in advertisements as a desirable feature of many products and services such as affordable housing, affordable automobiles, or affordable health plans. But while dictionaries and other reference documents define *afford* and *affordable,* they do not define *affordability*, and if affordability is acknowledged, it is described in the context of ability to afford something. Those references tend to reinforce the conventional wisdom and usage of the term.

In contrast, this dissertation addresses affordability in a much broader and deeper context than ability to pay the price of a product or service. Here, affordability is considered an economic benefit that accrues to customers in the same context that return on investment is an economic benefit that accrues to producers. To that end, this dissertation leverages a precise definition of affordability, with a process for modeling affordability as fitness, to develop and support the conjecture that affordability is the benefit that accrues to consumers, and to determine how industrial and systems engineering approaches can be used to design, develop and produce affordable products and systems. The dissertation also identifies specific industrial and systems engineering approaches that can quantify and measure affordability.

As a result, this dissertation details new contributions to the Industrial and Systems Engineering literature. The overall contribution is a unified approach for systematically developing a broad range of affordable products or improving their affordability; and a consistent, effective method for quantifying, measuring and assessing affordability. This dissertation covers gaps in the complexity, systems engineering, performance measurement and system dynamics literatures with respect to designing, developing and producing affordable products and systems that have not been addressed before. Within this context the dissertation features three essays, each of which is a chapter in the dissertation that contributes something different and unique.

Essay 1 provides a conceptualization of affordability as fitness. It presents the concept of fitness for biological systems, which is used to develop the concept of fitness for technological systems. This includes the development of fitness functions used to characterize and quantify affordability as fitness. Within this context, it describes the use of fitness landscapes to represent that fitness. It incorporates the fitness landscape framework, to introduce the concept of path dependence as an important issue that needs to be addressed within the systems engineering design process to enhance affordability. Within that same framework, this essay suggests that data envelopment analysis (DEA) is an appropriate approach to quantify fitness and consequently affordability.

Essay 2 extends Sterman's system dynamics representation of path dependence by applying it to the conceptual, preliminary and detailed design phases of the systems engineering process. The essay uses this model to explore specific relationships between systems design activities and positive and negative feedback that exist within each of the three systems design phases. It offers strategies, techniques and insights that decision-makers can use to analyze the incidence and effects of path dependence during each systems design phase and to make associated policy decisions. It suggests that decision-makers should focus on interventions to determine initial design directions involving technologies and exemplar products, to evaluate feedback regarding design and test quality, and to explore alternative paths during the design process that may resolve impending design issues such as lock-in to inferior or costly designs or offer a more affordable end product. Thus essay 2 provides new approaches to product and service design and development that can be incorporated in systems engineering courses and the supporting literature.

Essay 3 addresses what has heretofore been a significant gap: the ability to measure affordability. It provides a mapping between the efficiency literature and the fitness landscapes. It argues that the production axioms in production theory do not violate key characteristics of fitness landscapes regarding input and output correspondence, closedness and convexity. The essay describes an innovative application of DEA as it relates to affordability. This application shows that the DEA output of relative efficiency is a measure of relative fitness, and thus affordability, of projects being evaluated; and indicates that DEA accelerates the evaluation process, reduces potential evaluator bias, and increases the probability that affordable projects will be selected.

1.2 Background of Research

In the mid-1990s the Department of Defense (DoD) established the requirement for weapon system acquisition officials to review new system affordability at specific acquisition milestones. But affordability was not precisely defined at the DoD level and it largely was left up to the military services to determine how to make systems affordable. In response to the DoD requirement to review new system affordability during acquisition milestone reviews, the Assistant Secretary of the Navy for Research and Development challenged the Office of Naval Research (ONR) in 1995 to initiate an approach to develop affordable Navy systems. In response to this challenge and with the approval and support of the Deputy Chief of Naval Research, the ONR Industrial Programs Department initiated an Affordability Science research program. The objective was to establish a foundation for Affordability Science by defining affordability, launching research and development efforts to develop affordability concepts, technologies and methods, and by characterizing affordability as a major benefit that accrues to the customer[1]. Visits to prominent academic institutions helped establish the foundations of an interdisciplinary science and contributed to structuring the Affordability Science program. Subsequently, ONR funded the Affordability Measurement and Prediction Program (AMPP) to develop Affordability Science[2]. Over 80 affordability measurement and prediction projects were funded and conducted by principal investigators from the academic, industrial, consulting and government communities.

[1] The Affordability Science program was established in 1995 under the leadership of Dr. David Moran, the ONR Code 362 Director. For over 10 years, the author was a major contributor to the development of the program and conducted much of the research described in this dissertation.

[2] The program was established under the direction and management of Ms. Katherine Drew, a member of the affordability research team and the ONR Industrial Programs Department.

While this author conducted AMPP studies of processes that complex adaptive systems use to increase their fitness, and the results of these studies indicated methods for improving the affordability of complex technological systems, the problem remains that a unified approach to systematically develop a broad range of affordable products or improve their affordability is lacking. Furthermore, a consistent, effective method for quantifying, measuring and assessing affordability has not been developed. The recent research and unique contributions reflected in this dissertation were motivated by those unfulfilled objectives when the AMPP was terminated in 2006. This dissertation has at least partially filled those remaining gaps by describing a unified approach to develop affordable products or improve their affordability, and by developing a consistent, effective method for quantifying, measuring and assessing affordability.

1.3 Organization of Dissertation

The main body of the dissertation is organized into three chapters that contain the three essays described above. Chapter 2 lays the groundwork for a unified approach to measuring and assessing affordability. It establishes a baseline of affordability definitions, concepts and descriptions; discusses modeling affordability as system fitness; develops affordability fitness functions; explores the impact of path dependence during systems engineering and methods to maximize affordability by leveraging path dependence benefits; and briefly describes how fitness can be modeled, measured and analyzed using DEA.

Chapter 3 describes and characterizes details of path dependence, expanding on its introduction in chapter two and using systems engineering terminology. After discussing the path dependence phenomenon, it employs a conceptual model to explain the dynamic sequence of path dependent design and feedback events during system development. It describes elements of the systems engineering design process that affect path dependence and shows how path dependence can influence the outcomes of that design process. It concludes with interventions for overcoming the negative effects of path dependence and for taking advantage of its positive effects using some of the methods discussed in Chapter 2.

Chapter 4 focuses on measuring affordability as fitness. It describes fitness landscapes that were introduced in Chapter 2, and explores the use of these fitness landscapes to quantify and measure technological system fitness of technological systems. It describes DEA principles and the use of the DEA model to evaluate technological efficiency using fitness functions developed in Chapter 2. It investigates the possibility that the DEA solution space can be mapped into a fitness landscape and, if fitness landscapes can allow for the existence of production axioms, these fitness landscapes can be evaluated using DEA. Chapter 4 includes a case study, where DEA is used to rank the relative fitness of U. S. Department of Defense corrosion research and development projects submitted annually for selection and funding. This last chapter in the main body of the dissertation also presents a mathematical formulation for measuring fitness that can be a useful alternative to DEA.

The conclusions and recommendations in Chapter 5 offer a number of opportunities for further investigation into methods to develop affordable new systems and improve the fitness of existing systems. Likewise, new research into the use of DEA and other fitness landscapes to improve and measure fitness can add substantial contributions to the engineering state of the art. The results of the research performed in conjunction with this dissertation and the unique contributions to the profession documented herein could also be valuable in expanding the Virginia Tech industrial and systems engineering curriculum and adding course content to existing industrial and system engineering courses.

2. Modeling and Measuring Affordability as Fitness

Abstract

In this paper we expand to a broader concept of affordability – one of fitness to perform at the level of quality required by the consumer, to perform at that level whenever the product or service is used, and to do so with minimum consumption of resources. We conceive this concept of affordability for technological systems by using the complexity sciences concept of fitness as the metaphor for technological systems' fitness. This representation of affordability as fitness allows for analytical methods that facilitate the development of affordable products and services and for the quantification and measurement of affordability. As examples we discuss the existence and impact of path dependence in the design and development of affordable products and services and illustrate the use of an approach grounded in production theory (data envelopment analysis) as a framework to measure technological system fitness.

Key words:

Affordability; fitness; systems engineering; fitness landscapes: fitness functions; coevolution; coadaptation; path dependence; lock-in; data envelopment analysis.

2.1 Introduction

Consumers are the ultimate decision-makers during the acquisition of products or services. These consumers, who range from organizations as large as the Department of Defense to units as small as families and single individuals, must choose what they are going to purchase and determine how much they are willing to pay. On the other hand, producers, who are primarily dedicated to maximizing economic benefits that result from the sales of goods and services, must choose what well-established methods they will use to achieve desired economic returns, and which approaches they will use to measure them. So questions arise as to which economic benefits should accrue to consumers as a result of these sales transactions, how these benefits can be achieved, and how consumer benefits could be measured.

The Department of Defense (DoD), in the mid-1990s, may have answered the question regarding what benefits accrue to the customer when, as arguably the largest customer in the nation, they required weapon system acquisition officials to review new system affordability at specific acquisition milestones. But affordability was never precisely defined at the DoD level and it largely was left up to the military services to determine how to make systems affordable. Since then, affordability has been more precisely defined, concepts and approaches have been developed, and measurement and prediction methods have been conceived and analyzed [1].

The primary objective of this paper is to introduce a broader concept of affordability – one of fitness to perform at the level of quality required by the consumer, to perform at that level whenever the product or service is used, and to do so with minimum consumption of resources. In order to support this broader concept of affordability we develop and support the conjecture that affordability is the benefit that accrues to consumers, describe how systems engineering methods are available to design, develop and produce affordable products and systems, and identify systems engineering analytical methods that can quantify and measure affordability. In particular this paper argues that affordability can be modeled as system fitness, that the complexity sciences [2] provide a conceptual basis for modeling affordability as fitness, that the complexity sciences' concept of path dependence [3] can be applied to the systems engineering process [4] for the design and development of affordable systems, and that data envelopment analysis [5] is a viable approach for modeling, measuring and analyzing affordability.

The author builds the case for modeling affordability as fitness from the foundation established by authors such as Kauffman, Holland, Arthur, Frenken and Altenberg. The results of their research and development of complex adaptive system behavior and fitness, conceptualization of fitness landscapes and path dependence, and use of fitness landscapes to assess and improve biological and technological fitness are applied by the author to the problem of developing a unified approach to developing and improving product affordability, and to quantifying and measuring the affordability of technological systems.

2.1.1 Background and Context

In 1995, when the DoD established the requirement to review new system affordability during acquisition milestone reviews, the Assistant Secretary of the Navy for Research and Development challenged the Office of Naval Research (ONR) to initiate an approach to develop affordable Navy systems. In response to this challenge, and with the approval and support of the Deputy Chief of Naval Research, Dr. David Moran of the ONR Industrial Programs Department initiated an Affordability Science research program. This program established a foundation for Affordability Science by defining affordability, launching research and development efforts to develop affordability concepts, technologies and methods, and characterizing affordability as a major benefit that accrues to the customer[3]. The idea that affordability is a benefit that accrues to the customer became an underlying principle. The ONR Affordability Science program identified affordability disciplines, technologies and methods; integrated them into a body of knowledge that characterized the affordability of goods and services; quantified these characteristics; and presented a roadmap for achieving product affordability. It also focused on measuring the affordability of existing products and predicting the downstream affordability of products being designed, developed or modified.

[3] The author was a major contributor to this initiative.

An Affordability Measurement and Prediction Program (AMPP) became the primary approach to develop Affordability Science.[4] The AMPP, created in 1997 to develop a science for evaluating or predicting the current and future affordability of key Navy research and development (R&D) products and services, was a viable, productive research program for over eight years. The primary thrust of the AMPP was to develop advanced, science-based generic affordability trade-off approaches that transcended the conventional cost estimating practices. Over 80 affordability measurement and prediction projects were funded and conducted by nearly 20 principal investigators: principal investigators from the academic, industrial, consulting and government communities. One of these projects studied complexity sciences concepts, and some of the processes that complex adaptive systems use to increase their fitness. Complex adaptive systems are complex, self-organizing systems composed of agents that behave and interact according to internal rules, and adapt to environmental changes and other adaptive agents by changing these rules. [6] [7]. The results of the complex adaptive systems study suggested methods for improving the affordability of complex technological systems based on the characteristics and behavior of complex adaptive biological systems.

The objectives of the AMPP were never fully realized, and the shortfalls in the program became primary objectives of this research. More specifically, the insights provided by the studies of complex adaptive systems concepts and behaviors stimulated the search for methods to model affordability as fitness and to develop the means to measure that fitness. The results of this search are documented in this essay.

2.1.2 The Problem

The AMPP produced a number of studies and methodologies that addressed two primary objectives. But the former project manager of the AMPP recently observed that, while some AMPP projects reflected effective methods to develop a specific genre of affordable products, the problem remains that a unified approach to systematically develop a broad range of affordable products or improve their affordability is lacking. Furthermore, a consistent, effective method for quantifying, measuring and assessing

[4] The program was established under the direction and management of Ms. Katherine Drew, a member of the affordability research team and the ONR Industrial Programs Department

affordability does not exist. [8] Thus, the major objective of this paper is to lay the groundwork for a unified approach to measuring and assessing affordability.

This paper is organized in four sections to address this objective. Section 2.1 establishes a baseline of affordability definitions, concepts and descriptions. In this section, the question of what benefit accrues to the customer is presented. Section 2.2 discusses the primary conjecture that affordability can be modeled as system fitness. In this section, the foundation for developing a unified approach to affordability development and improvement is provided, and the idea that affordability is the benefit that accrues to the customer is reinforced. Section 3 discusses the conjecture that the design, development and engineering of affordable technological systems are path dependent processes. In this section we suggest a method for developing affordable products and summarize systems engineering methods that can be applied to maximizing affordability as a benefit that accrues to the customer. Section 4 addresses the conjecture that fitness can be modeled, measured and analyzed using data envelopment analysis (DEA) [5], which is a linear programming based approach grounded in microeconomic theory that computes the relative efficiency of alternatives based on the value of key input and output variables common to every alternative. In this case, the analysis of key affordability variables can be used to indicate the relative fitness of each alternative. Thus this approach potentially provides a method for quantifying, measuring and assessing affordability and reinforces the concept focused on the measurement of affordability as a benefit that accrues to the customer.

2.2 Affordability and System Fitness

2.2.1 Affordability Definition, Concepts and Description

The basic affordability definition is derived from Webster's definition of affordability and from the associated concepts of system fitness. Webster [9] defines affordability as the capacity to bear the consequences of implementing a decision without serious detriment. Conventional wisdom usually assumes these consequences to be financial costs. For example, the Department of Defense usually considers an affordable system as one that has acceptable life cycle costs [10]. Individual citizens often define an affordable automobile as one for which they have the means to pay its acquisition price. However, institutions and individuals do not decide to acquire systems, products and services just for the privilege of spending money. They almost always impose conditions and constraints on these acquisitions, and these conditions and constraints are associated with how and when the system, product or service performs.

From a practical standpoint, a decision-maker decides to acquire a system, product or service that will perform some required function. The decision-maker expects that system, product or service to perform at some minimum level of quality any time that it is needed. In the quality management world, one definition of quality is fitness for use [11]. Thus, system, product or service performance and availability are key fitness parameters of their affordability, along with the required resources (costs) that are associated with systems operations or the provision of products and services.

The fact that decision-makers might expend resources to satisfy some requirement or desire, regardless of their ability to pay the purchase price, should raise serious questions regarding the ability to pay as the sole measure of affordability. Consider the following scenario in the context of Webster's definition of affordability. A consumer decides to purchase a product for which he has three brands from which to choose. The first brand cannot *perform at the minimum level of quality required by the consumer*. The second brand cannot *perform its function whenever the consumer requires its use*. The third brand will require the consumer to spend *unacceptable life cycle operating costs*. In each case the product is not affordable according to Webster's definition, regardless of the consumer's ability to pay.

Affordability is that characteristic of a product that enables decision-makers to procure it when they need it, use it to meet their performance requirements at a level of quality that they demand, use it whenever they need it over the expected life span of the product or service, and procure it for a reasonable cost that falls within their budget for all needed products or services. The above scenario and its consequences formed the foundation for this definition of affordability that was established at the beginning of the Affordability Science Program [12]. This remains the definition of affordability, and is used as such throughout the remainder of this paper.

The 2009 *Naval S&T Strategic Plan* [13] lists total ownership cost as one of thirteen S&T (Science and Technology) focus areas. On page 25, the plan states, "This focus area is dedicated to significantly increasing the affordability of current and future naval systems by reducing Total Ownership Cost while maintaining or improving system performance and platform availability to execute assigned missions." Based on the above affordability definition and the Naval S&T Strategic Plan description, an affordable technological system can be described as one that *performs at an optimum level to accomplish its purpose, remains available to perform when needed, and can be procured and operated within reasonable cost utility parameters*. Achieving an optimum level of performance with respect to performance, availability and cost implies that improvement in each of the key affordability variables associated with these concepts increases affordability. Vectors of performance, availability and cost variables can represent affordability. But since an increase in cost results in lowered affordability, it is more practical to quantify cost in terms of resource conservation, which will increase affordability as resource conservation increases. For example, determining savings, cost avoidance or return on investment for a particular requirement would produce a resource conservation value for that requirement where an increase in that value reflects improvement. This definition is consistent with the definition used by the Affordability Science Program stated in the previous paragraph. These definitions, concepts and descriptions of affordability provide a framework for modeling affordability as product fitness for use, for developing affordable products, and for quantifying and measuring affordability. The next three sections address these three specific issues.

2.2.2 Modeling Affordability as Fitness

The overarching conjecture that the affordability of technological systems can be modeled in the same way as the fitness of natural systems [14] is an approach that heretofore has not been extensively pursued in the literature. Natural systems are complex adaptive biological systems that have the genetic capability to produce surviving offspring. Natural system fitness can be defined as the combined inherited characteristics that produce strength and usefulness in the offspring – the stronger and more useful, the greater the fitness [6]. An associated conjecture is that affordable technological systems are achieved when selected attributes of the systems dynamically co-evolve with the attributes of interacting systems (including the environment), and this interaction causes the co-evolving systems to dynamically adapt to each other – a process Kauffman calls co-adaptation [14].[5] These dynamics include self-organization, close coupling, and feedback with response, which are characteristics of what Sterman describes as dynamic complexity [15]. These conjectures raise several important questions associated with modeling affordability as fitness. Does natural system fitness provide a model of fitness that can be applied to affordability as defined? What schemata can be used to represent and analyze technological system fitness and thus affordability? Can product fitness be characterized by affordability fitness functions? [16] In this context, fitness functions are the system operating capabilities that feature quantifiable, key attributes that guide the search for increased fitness in a search space of optimal or near optimal affordability solutions. How can we select product attributes, associated with affordability fitness functions that contribute to product fitness? The review of the above questions and preliminary research regarding complex adaptive systems that we are documenting in this section provide some answers to these questions and some directions in which to pursue further research.

If we revisit the AMPP affordability definition, availability implies that the system is not only sustainable[6] but is adaptive to ensure readiness under changing conditions. Reasonable cost utility implies judicious use of scarce resources. If we observe the characteristics of a natural system, we find that it performs functions at an optimum level for survival and growth, it performs those functions when necessary, it consumes minimal resources to improve or maintain fitness, and it adapts to environmental changes. This metaphor implies that complex adaptive natural systems are inherently affordable and their characteristics could provide insights for the affordability of technological systems. Conceptually, we could describe affordable technological systems in the same terms as highly fit complex adaptive natural systems. If this is so, product affordability might be defined by technological system fitness, where fitness attributes associated with

[5] Webster defines coevolution as "evolution involving successive changes in two or more interdependent species that affect their interactions."

[6] Webster defines sustainable as capable of being sustained, in other words capable of resisting depletion or permanent damage. In the context of this paper, a sustainable system is one that can be used effectively for a prolonged time period.

specific technologies, materials or processes offer the best set of variables to be evaluated as affordability metrics. Furthermore, if we map the attributes of complex adaptive natural systems to affordable technological systems, we find striking life-cycle similarities [1]. For example, natural systems must overcome vulnerabilities during creation, achieve growth using available nutrients, sustain life using scarce nutrients, respond cyclically to a biological clock, achieve a robust survival structure, self-regulate, execute timely repairs to continue effective functioning, perform a useful ecological function, and procreate effectively to assure species survival. An adaptive technological system must overcome R&D vulnerabilities, be developed and implemented using available resources, sustain operation using scarce resources, respond to repeated operational cycles, self-regulate, undergo timely repair to continue effective operation, perform a useful ecological function, and be effectively modified for use as a next generation system.

2.2.3 Improving Fitness

The previous subsection suggests that characteristics of natural or complex adaptive systems might be useful models or metaphors for developing affordable technological systems. John Holland [6] describes complex adaptive systems as systems composed of interacting agents that adapt by changing their strategies as they accumulate experience. The product of this adaptation is often unusual, unexpected, and even miraculous characteristics and capabilities, a process Holland describes as emergence. He describes emergence as the application of a small number of rules or laws to a combination of simple building blocks in a system that produces higher-level systems of unexpected and unusual complexity [17]. In biological systems, adaptation enables an organism to achieve greater environmental fitness. Similarly, in technological systems, adaptation might enable these systems to effectively respond to dynamic changes in the operational environment. This suggests that complex adaptive systems, characterized by emergent qualities that enable them to achieve unexpected levels of fitness, could represent a model of fitness that can be applied to product affordability [17].

Dynamic changes in system fitness, such as improving performance while using fewer resources, can be depicted on fitness "landscapes" in order to analyze, improve and measure resulting technological fitness and affordability. Metaphorically, these landscapes have peaks and valleys, and the fitness function variables define the dimensions of the landscape. In his book *At Home in the Universe*, Kauffman [14] describes a rugged fitness landscape as an ideal structure with which to pursue biological fitness. He observes that technological evolution can be depicted as a search on rugged landscapes. This description and observation suggest that biological evolution and fitness can be a metaphor for technical evolution and fitness – a metaphor that is pursued in detail in this paper.

As Kauffman points out [14], systems increase fitness through searching the fitness landscape and hill climbing. Systems change their location on the fitness landscape by changing values of system traits or attributes. The shape of the fitness landscape has a significant effect on the ability of a system to search for and attain greater heights and thus improve its own fitness. Kauffman introduced the NK landscape model to represent the shape and degree of ruggedness of fitness landscapes, where N is the total number of system attributes and K is the number of individual attribute characteristics with which each of the N attributes is epistatically coupled (operationally linked). The term epistatic coupling, or epistasis, refers to coupling between genes, where the fitness of a gene located at a given place on a chromosome is affected by genes located at other places on the chromosome. In this case, it is used to describe the effect that system attributes could have on other system attributes. These fitness landscapes may be correlated, where peaks of similar altitude are grouped together, or random, where peaks of different altitudes are randomly distributed across the landscape. The degree of ruggedness (from correlated to random) depends on the values of N and K: increasing N reduces correlation and increasing K increases randomness and thus ruggedness. Correlation represents the proximity of landscape peaks to each other, so if K remains constant, fitness peaks are spread more widely across the landscape. Ruggedness refers to the relative "altitude" of the peaks, so if N remains constant, the peaks become higher. When both N and K increase, the decrease in correlation and increase in ruggedness configure the landscape in such a way as to make fitness increase, but the likelihood of finding rugged peaks less and less likely.

Kauffman associates the K parameter with the transition of dynamical systems from order to chaos, where K = 0 represents total order and K = N – 1 represents complete chaos. When K = 0, there is but one peak on the landscape and when K = N – 1 the landscape is totally random. Thus the landscape transitions from order to chaos, and the phase transition – a rather rapid shift from order to chaos – occurs at K = 10 according to Kauffman [14]. The transition zone is called the zone of complexity – a zone where "the very highest fitness occurs" at the edge of chaos.

Kauffman also describes coupled landscapes where one fitness landscapes interacts with another fitness landscape. In *The Origins of Order,* Kauffman [18] describes co-evolution as a process of adaptive moves that deform these coupled NK landscapes of interacting systems. Each system's fitness and fitness landscape depend on the other systems' fitness. As co-evolving systems co-adapt, and the shape of a fitness landscape changes, the degree of fitness improvement or degradation in a particular system will be dictated by the ability of that system to alter existing attributes or generate new attributes that comply with the changing shape. If attribute changes enable the system to improve its position on the new landscape, the system becomes fitter.

Technological systems can rapidly achieve high fitness through coevolution and coadaptation in the zone of complexity, where there is sufficient epistatic coupling to trigger new, novel, diverse varieties of goods and services and create niches for even more varieties [14]. This suggests that it would be useful to seek or create conditions conducive to achieving high fitness levels and to drive technological development to the edge of chaos to produce affordable customer products and services. Coevolutionary conditions and characteristics, including moderate epistatic coupling between developing technologies and their environment, could enable the development of new systems in the zone of complexity. So it appears that fitness landscapes are appropriate schemata to represent and analyze product fitness and thus product affordability.

Frenken [2] points out that technology fitness landscapes are useful models upon which to conduct local search strategies for technological evolution. Such local search strategies outperform global search strategies because bounded rationality [2, 19] constrains the ability of designers and engineers to generate all possible solutions to complex optimization problems, and economics constrain the ability to perform exhaustive global searches. Kaufmann's NK landscape or Altenberg's generalized NK landscape [20] are useful models upon which to conduct adaptive walks or hill climbing toward local peaks on the landscape, in order to increase technological fitness. Thus, an adaptive walk on a fitness landscape, where an attribute value is changed and the resulting product fitness evaluated at each step until maximum fitness is reached, can suggest affordable product designs.

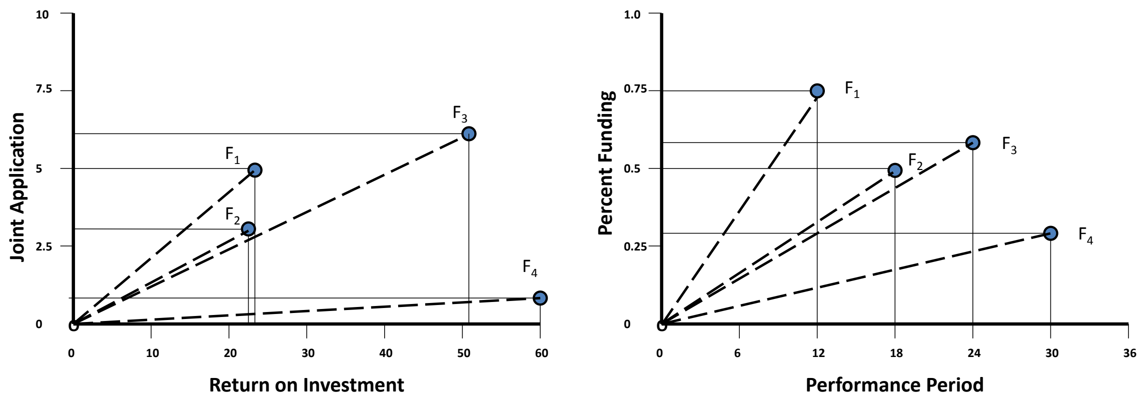

Figure 1a. Normal Fitness Landscape

Figure 1b. Inverse Fitness Landscape

Figure 1. Fitness Landscapes with Two inputs and One Output

Figure 1 shows a simple two-input, one-output fitness landscape, using Table 16 data in Appendix B. Figure 1a shows four vectors, OF_1, OF_2, OF_3, and OF_4 that correspond to DMUs AF01, AF07, NS08, and AR07. OF_4 is the fittest vector since the radial distance of vector OF_4 is the longest of the four vectors.[7] The shortest vector, OF_2, is the least fit. In Figure 1b, vectors OF_1, OF_2, OF_3, and OF_4 correspond to Table 16 DMUs AF01, AF07, NS08, and AR07. Figure 1b is an inverted landscape, since the highest fitness is associated with the lowest percent of funding and the shortest period of time. Vector OF_2 is the shortest vector and has the highest fitness of the four vectors. OF_4 is the longest and therefore the least fit vector.

Frenken suggests that exemplar technologies be used in the search to reduce the number of search paths required to achieve fitness. And he describes a function space search

[7] Vector length is computed as the hypotenuse of a right triangle $F_n = \left(\sqrt{a^2 + b^2}\right)$ where a and b are the two inputs and F_n is the output. Figure 1a vector values are $OF_1 = 24.9$, $OF_2 = 23.7$, $OF_3 = 51.9$, and $OF_4 = 60.2$. Figure 1b vector values are $OF_1 = 12.02$, $OF_2 = 18.01$, $OF_3 = 24.01$, and $OF_4 = 30.00$.

where specific preferences associated with the most important functions allow designers to narrow their focus to those input variables that have the most impact on the fitness of those functions [2]. These approaches support the limitation of such searches to the zone of complexity, and indicate the need for development of affordability fitness functions to aid in such limited searches.

For example, the development of supersonic aircraft control systems was based on exemplar fly-by-wire and sensor-based control technologies. And the discovery that these aircraft performed best when they were slightly unstable (in the zone of complexity at the edge of chaos) led to a system that enhanced pilot performance by providing the assistance necessary to enable control of flight in the unstable regime [21].

2.2.4 Fitness Functions

Prior research [1], the definition of affordability, and the concept of affordability as fitness suggest that four fitness functions form the structure of an affordability fitness landscape, where key attributes related to these fitness functions are variables that are the dimensions of the fitness landscape. Thus the vectors formed by the key variables associated with each fitness function represent the affordability of the system being considered. The first fitness function is performance – the optimum activity to allow the system to achieve its reason for being, to increase its fitness, and to contribute to maintaining other fitness functions. The second fitness function is vitality – the propensity and activity to survive, to resist damage or destruction, and to remain sustainable by means of maintenance and damage repair. The third fitness function is adaptability – the ability and activity to change other fitness functions in response to co-evolving systems in order to maintain or increase fitness. And the fourth fitness function is resource conservation – the ability and activity to constrain consumption of resources to only those resources necessary to maintain a required fitness level.

A common consumer product, the household vacuum cleaner, can illustrate this concept of affordability as fitness and the use of fitness functions. In order to measure the affordability of a vacuum cleaner, a consumer selects those features that meet that customer's needs and classifies them by affordability fitness function, such as shown in Table 1. For example, strength, reliability, durability, maintainability and safety are features of the vitality fitness function that enables the vacuum cleaner to resist damage or destruction, and to remain sustainable. The importance of the features and fitness functions can be weighted after which the consumer ranks how well each feature contributes to the fitness function. The results are used to quantify the value of each fitness function, and those values are used to measure the affordability of each vacuum cleaner considered and rated by the consumer.

Performance	Vitality	Adaptability	Resource Conservation
Keep soil in container	Air flow capacity	Do stairs	Price
Strength	Strength	Pick up pet hair	Weight
Reliability	Reliability	On-off switch for brush	Replacement parts cost
Durability	Durability	Height adjustment	Consumable parts cost
Effective cleaning	Environmentally friendly	Cleaning path width	Repair cost
Easy emptying of soil	Ease of storage	Crevice tool	
Quietness	Maintainability	Upholstery tool	
Full container indicator	Safety	Integrated extension wand	
Suction	Filter	Power nozzle	
Power	Power	Suction control	
Maneuverability/handling		Pet brush	
Head light		Cord length	
Retractable cord		Hose length	
Edge cleaner		Versatility	
Dirt Sensor		Ergonomic design	
Self propelled			

Table 1. Features of Vacuum Cleaners Customers Could Care About

The fitness functions in Table 1 are the dimensions of a vacuum cleaner generalized NK fitness landscape, where a fitness vector represents the combination of fitness function values associated with each specific product. A vector is a quantity with both magnitude and direction, and its location and value in the landscape is determined by its direction from where all dimensions intersect at their origin to its distance from each variable’s axis at that variable’s value [22]. A comparison of vector locations on the fitness landscape reveals the most affordable vacuum cleaner. The most affordable vector sum is

$$max \sum_{i=1}^{n} P_i + V_i + A_i + R_i \;\; i = 1, 2, 3, \ldots, n$$

where n = the number of brands, and P, V, A, and R are fitness function values.

The generalized NK fitness landscape does not use the K parameter to indicate epistatic coupling, but does reflect epistatic coupling by mapping attribute characteristics to function characteristics as described in Chapter 4, Section 4.2. Strength, reliability, durability and power affect both performance and vitality fitness functions and the vector sum for each reflects this epistatic coupling.

Vacuum cleaner manufacturers could traverse such a landscape in search of competing products that exceed their product's fitness. Those with similar attributes might feature exemplar technologies that would improve the fitness of their product. The impact on overall product fitness by using new or exemplar technologies could be evaluated on the landscape and show the degree of improvement and relative fitness compared to competing products.

Vector distance is one type of distance function that can be used to evaluate the affordability of competing alternatives such as vacuum cleaner brands. Other distance functions that might be used are the number of binary variables by which two strings (vectors in this case) differ, called hamming distance [23], and the correlation coefficient between vector values of a fitness landscape and rankings of products in publications such as Consumer Reports [24, 35].

Vacuum cleaner product attributes can be represented on a fitness landscape where attribute traits are the dimensions of the landscape, and the attribute is a vector of these traits. Some of the features in Table 1 are attributes, and each of these attributes has traits or characteristics that dictate the quality or fitness of that attribute. Increasing or decreasing the value of a product trait changes the vector value (fitness) of the attribute. For example, one of the traits of vacuum cleaner suction is the efficiency of the motor that causes reverse airflow [25]. Increasing the reverse airflow increases suction and thus improves that attribute's fitness.

Kauffman [14] described the process of changing system fitness as the alteration of a system's attributes. As described above, the degree to which a particular key fitness attribute contributes to each fitness function defines that attribute's location on the system's fitness landscape. The relative strength of a key fitness attribute may be affected by epistatic coupling with other key fitness attributes that could increase or decrease its strength. An attribute's contribution to system fitness need not be positive – a strong attribute could have a negative effect on one or more other key fitness attributes and reduce overall system fitness. And, since each attribute is likely to affect multiple fitness functions, it is possible that a specific attribute could have a positive impact on one fitness function while having a negative impact on another. For example, a strong, powerful motor would increase vacuum cleaner suction and durability, which would improve performance and vitality. But the increase in weight would reduce maneuverability and design flexibility thus decreasing adaptability, and the added cost and weight would reduce resource conservation.

Table 1 provides examples of epistatic coupling of vacuum cleaner features or attributes. Strength, reliability and durability are depicted as attributes for both performance and vitality fitness functions. The traits associated with these attributes affect the attributes in different ways. For example, a durable suction hose might increase its service life but the material that makes it durable might make it inflexible and reduce the airflow rate. The NK landscape was conceived to reflect this coupling between traits at the lowest level of detail, between attributes at the next higher level of detail, or between key fitness variables at the highest level of detail. The “N” in NK landscapes represents the number of traits, attributes or key fitness variables (as well as the number of dimensions of the fitness landscape), while the “K” reflects the average number of traits, attributes or key fitness variables epistatically coupled. In Table 1, K = 4, which is the average number of epistatic couplings between the attributes within the four functions. The effect of adjusting traits on coupled attributes or the effect of adjusting attributes on coupled key fitness variables can be evaluated on an NK landscape [2, 14, 18].

Kauffman’s NK landscape has a limitation that is overcome by Altenberg’s generalized NK landscape. Altenberg’s model consists of N elements (key input variables) and F functions (key output variables), where Kaufman’s model requires the number of elements to equal the number of functions. In Altenberg’s model, a key input variable can influence any number of key output variables and a key output variable can be influenced by any number of key input variables. This means that the generalized NK landscape does not use the K epistatic coupling variable and that the number of elements does not have to equal the number of functions. This allows vectors of input variables associated with each function to be represented on a fitness landscape and to be used to evaluate the fitness of alternative technological systems or to improve the fitness of a specific system

[2, 20]. Altenberg's model can be expressed mathematically as a vector for each function F:

$$F_j = \sum_{i=1}^{n} N_{ij}\, w_{ij} \; j = 1,2, \dots m \; i = 1,2, \dots n$$

where

$n =$ number of elements N

$m =$ number of functions F

N_{ij} = input elements affecting function F_j

w_{ij} = weights applied to input elements (if any)

F_j = output vector of N_{ij}

Kauffman also introduced the concept of coupled fitness landscapes, where a set of fitness landscapes is joined at the next higher level to reflect and assess coevolution and co-adaptation caused by the epistatic coupling of traits on one landscape with traits on the other landscape [14]. For example, those vacuum cleaner attributes that have an epistatic effect on other vacuum cleaner attributes would be the dimensions of a landscape to determine the value of key variables. But each of these coupled attributes would have its own fitness landscape, with vacuum cleaner traits associated with each attribute as the dimensions of those landscapes. Thus, a fitness landscape of various characteristics of residences and buildings using vacuum cleaners would be coupled with a vacuum cleaner fitness landscape, to evaluate how specific vacuum cleaner attributes interact with specific characteristics of those residences and buildings. The effects of epistatic coupling between traits would affect attributes, and the changes in those attributes would affect key variables with which each attribute is coupled. By analyzing these coupled effects, the design of a vacuum cleaner could be improved, or a decision-maker could analyze the resultant fitness of given vacuum cleaner configuration. The above mathematical formulation could be used to evaluate the impact of traits (input elements N) on attributes (output functions F) at one level of taxonomy and of attributes (input elements N) on key variables (F) at a higher level of taxonomy. Thus, the most affordable configuration could be expressed as:

$$max \sum_{j=1}^{m} F_j \quad = max \sum_{i=1}^{n} \sum_{j=1}^{m} \; N_{ij} \, w_{ij}$$

The interactive process between traits, between attributes, or between the key fitness variables has been termed co-evolution. Technological systems co-evolve as the system attributes interact during design, development and operation. Kauffman [18] describes co-evolution as a process of adaptive moves that deform the coupled NK landscapes of the interacting systems. In other words, changing an epistatically coupled trait will affect each of the attributes with which that trait is associated. That will change the position of the key variable vector associated with those attributes, thus "deforming" the landscape of key variables. At the same time, the vector of each attribute is changed, deforming each attribute's landscape. So each system's fitness and fitness landscape depend on the other systems' fitness. As co-evolving systems co-adapt, and the shape of a fitness landscape changes, the degree of fitness improvement or degradation in a particular system will be dictated by the ability of that system to alter existing attributes or generate new attributes that comply with the changing shape. If attribute changes enable the system to improve its position on the new landscape, the system becomes fitter.

Thus, co-evolution and co-adaptation are dynamic processes characteristic of evolving biological and technological systems. Biological systems do that naturally. But technological systems depend on some intervention to stimulate co-evolution and account for the consequences of co-adaption. This is a key concept in the design and development of products that can be used to develop more affordable products, such as better vacuum cleaners.

Methods for applying and evaluating key attributes are addressed in the two sections that follow. Although methods for identifying key attributes have been identified in working papers and reports during preliminary research [1], further research and experimentation with real products is needed to validate suggested analytical approaches or to develop new ones.

2.3 Developing Affordable Products

The previous sections provide some clues regarding how complexity science concepts and approaches might be used to develop affordable products. The ONR AMPP program also fostered the development of many affordable products and services, some of which were based on complexity sciences principles. However, this paper focuses on one complexity science-based concept as an approach to develop affordable products – the path dependence phenomenon and its effect on designing and developing affordable systems.

An important conjecture is that product fitness, or affordability, is influenced by path dependence during product development [2]. An associated conjecture is that path dependence can be used to positively influence and accelerate product fitness [26]. Products undergo development in a systems engineering technological evolution where the requirements are defined, the product is conceptualized and designed, and various stages of development are performed until a complete, functional product emerges. Sterman [15] defines path dependence as a system behavior pattern where small, random events in a system dominated by positive feedback determine the ultimate system state. Path dependence can produce positive or negative effects. Positive feedback can accelerate achievement of the most affordable design. But continuing along a path of positive feedbacks can cause the system designer to miss better solutions. So understanding the effects of path dependence, taking action to prevent its negative effects and taking advantage of its positive effects are essential in developing affordable products.

This section describes the underlying mechanisms that create, dictate and maintain path dependence, discusses the effects of path dependence on product development, and suggests actions to address its impact on affordability. It addresses several questions raised by the conjectures stated in the previous paragraph and the description of path dependence. Specifically, it describes how path dependence affects product fitness during its technological evolution; how path dependence can be measured at selected points during the technological evolution; and how the understanding of path dependence can be used to improve product fitness. In addition, this section discusses the selection of the technological development path prior to the onset of product development, and how it can be changed during the development process.

During conceptual design, preliminary design and detailed design; the three phases of the systems engineering life cycle process that precede system production, operation and phase-out [4], the specific product design outcome is determined by that set of design search paths that were followed. In other words, the design process is path dependent. Dynamic mechanisms create, dictate and maintain path dependence. Initial conditions define the start and direction of a path. During subsequent design steps, positive feedback influences the designer to continue on that path. Frequently, the design gets “locked-in” due to unforeseen external conditions that eliminate other practical alternatives. Hypothetically, the shortest overall path length should be the most affordable in terms of system design, if the desired level of product fitness is achieved. If the system designer avoids obstacles and random diversions, copes with the possible effects of co-evolution, and chooses the best set of search directions, product affordability should be achieved in terms of each fitness function described in the previous section. Modeling, simulating and testing path dependence in a typical design path should reveal the relationship between path length, system design affordability, and consequently product fitness.

During systems engineering and system design, metrics and mechanisms for providing feedback dictate the level and direction of path dependence. Requirements are derived from customer needs, and system level measures of effectiveness (MOEs) are established and quantified to evaluate how well each design alternative meets established requirements [4]. These MOEs must be legitimate and unambiguous because they will determine whether measurement feedback is positive or negative. Since product design co-evolves with product use and support, the product support infrastructure and product environment need to be identified and characterized since tradeoffs between product and support might change product attributes, and therefore fitness, as the landscape is reshaped.

During preliminary design, accurate specification and accurate measurement are critical. Path dependence resulting from positive feedback during simulation and testing can positively or negatively influence design decisions. If the MOEs, simulations and test methods are effective, design alternatives are likely to be accurately assessed and the correct design path indicated. However, if design assessments and tradeoffs are faulty, the wrong design path may be indicated – the designer may continue on a low fitness design path or erroneously take a new low fitness path. Successive positive feedbacks may mask the design's ultimate low fitness until late in the preliminary design phase or even the detailed design phase. At that point, it may be too expensive to search for and find a higher fitness path and the design may essentially be locked-in.

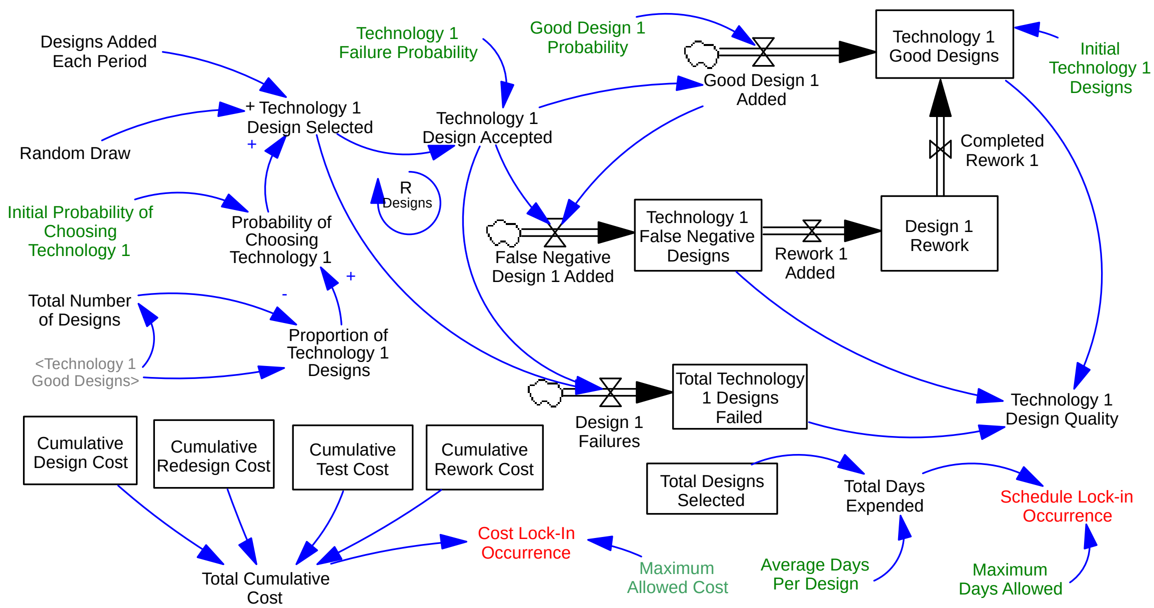

Figure 2. System Dynamics Model of Path Dependence During Systems Design [27]

Figure 1 illustrates lock-in to a single technology in the design reinforcing loop from technology 1 design selected, to technology 1 design accepted, to good design added, to technology 1 good designs stock, to total number of designs, to proportion of technology 1 designs, to probability of choosing technology 1, and back to technology 1 design selected. As long as positive feedback occurs throughout the reinforcing loop, there is a very high probability that technology 1 will continue to be selected. It also shows lock-in to cost and schedule as indicated by the red cost lock-in occurrence and schedule lock-in occurrence variables. If maximum allowed cost or schedule days are exceeded, lock-in will be flagged for management decision-making.

In the detailed design phase, each product component features its own initial condition and path direction. So, the starting point and direction for a component development path might reflect path dependence. Each in-process and completed item test presents an opportunity to evaluate the fitness of a product component. If the metrics and test methods are effective, the design is likely to be accurately assessed and the correct design path indicated. If the metrics and/or test methods are ineffective, the design may be erroneously accepted or rejected. If the error is detected far up the technological development path, it may be difficult and costly to trace the error to its source and even more costly and time consuming to change the path. Undesirable lock-in might occur if negative feedback dictates a new path that is prohibitively expensive, or a technology that is not sufficiently developed or supported. However, lock-in due to overwhelming high fidelity, positive feedback is desirable since the right technological path was selected.

The path dependent design process can be described as a process of hill climbing on an affordability fitness landscape. Before the climb commences, the systems designer chooses, often randomly, that starting point and design path that appear to offer the best chance of establishing a viable product design and of improving design fitness during the development process. The designer continues on that path as long as positive feedback indicates the correct design choice was made. For example, if functional test results of the motor selected for a new vacuum cleaner design are unacceptable, negative feedback indicates that progress is downhill, and the designer looks for and chooses a different path; perhaps a new motor. If feedback is positive, the designer continues on the same design path. If the vacuum cleaner motor as designed will not fit in the main vacuum cleaner housing, the designer encounters a design obstacle that dictates a change in direction or perhaps a retreat, so the designer also takes another path that incorporates a redesign. If a chance occurrence threatens the design, the designer may work around that threat or change direction. For example, if the design calls for some vacuum cleaner parts to be procured from a supplier, and that supplier goes out of business, the designer may have to change the vacuum cleaner design if the supplier is a sole source of the parts, or the designer may work around the problem by going to another supplier. In the latter case, the designer can stay on the same path. The further the designer travels along the design path, the higher he or she climbs, and the fewer the number of available upward paths. And, when a local peak is reached, there are no remaining upward paths. If the vacuum cleaner design has attained the desired level of affordability, hill climbing ceases and the design is complete. The positive feedback relationships are shown in Figure 1, where design acceptance indicates that inspection or testing has passed, or the design is good because an obstacle or random occurrence does not threaten the design. A local peak is reached when the design process is completed.

If the desired vacuum cleaner fitness is not achieved at that local peak, the designer must decide whether to accept the level of fitness achieved or look for a higher hill [2]. If it is too expensive to pursue another path, the design may be locked-in at this point. Or, if available technology will not support searching in other directions, the designer also may be forced to lock-in to this design. However, if further search is feasible, the designer might retrace the prior path and search for a new path to a higher hill and begin the upward climb to its peak. If the nearest higher hill is quite far though still visible, the designer may find a way (perhaps a new technology) to completely escape the path that led to the lower hill and jump to the base of that higher hill. For example, vacuum cleaner dirt containment bags have always had some drawbacks that decreased the overall fitness of vacuum cleaners. One manufacturer jumped off the design path at the turn of the century, and incorporated a new wind tunnel technology that enabled bagless vacuum cleaners [26]. That vacuum cleaner designer was able to climb a new path to the peak of that hill and achieve the desired fitness more quickly and easily, based on experiences while on the original path. When other manufacturers became aware of the technology, they started new bagless vacuum cleaner designs with the wind tunnel technology. So the jump to a new path broke the path dependence on traditional design for the original manufacturer of bagless vacuum cleaners and established a new starting point and direction for other manufacturers [28, 29].

This description of path dependence assumes a fixed landscape where the values of product fitness variables remain unchanged. But the development of each technological system affects other systems as they co-evolve, as described earlier in the vacuum cleaner selection example, and the shape of the fitness landscape changes. Available paths and local peaks shift causing changes in the points of highest system fitness and the ways to approach these points. Just when the product designer is about to reach a desired fitness level, a search along new or prior paths may be required due to co-evolution and the shifting fitness landscape. The new search might yield better fitness if higher peaks are attainable, or produce lower fitness because the co-evolving system reduced the altitude of available peaks on the fitness landscape. The worst case could be lock-in to a low fitness design because the changing landscape has eliminated some paths, and the designer is trapped on a low fitness peak or in a low fitness basin from which there is no escape [14, 18]. Therefore, during the design process, the initial design, changes to that design, and the final result are all dictated by the set of search paths followed.

The above description provides a foundation and structure for developing alternative strategies and techniques to address path dependence and its effects and to develop affordable products. The following interventions, derived from the process and impact of path dependence described in the literature, and from the results of system dynamics path dependence modeling, provide a framework for more detailed strategies in the context of this paper. They include the application of the system dynamics model illustrated based on Sterman's system dynamics formulations [15].

Model the complete path for a design phase to identify critical variables in the design path and assess the impact of positive and negative feedbacks at those and other points.

1. Establish clear, measurable requirements and high fidelity metrics for evaluating system fitness along the design path.
2. Choose initial conditions (including technologies and products) that will most likely positively influence the design path and produce desired system fitness.
3. Plan for and get frequent feedback to assess system fitness along the design path.
4. Quantitatively assess alternative paths when declining fitness or obstacles force a path change.
5. Evaluate the effect of random external influences along the design path and attempt to reduce or eliminate adverse impacts if changing the design path reduces system fitness.
6. Occasionally search the adjacent landscape and attempt to discover paths to higher peaks.

A number of alternative modeling approaches and techniques might be used to implement these strategies. For example, Sterman [15] describes the use of causal loop diagrams when analyzing the system dynamics of path dependence. This approach can characterize path dependent systems through identification of positive feedback loops that reinforce system fitness. It would be particularly useful for modeling the systems engineering conceptual, preliminary, and detailed design phases, to show the impact of path dependence on cost, schedule and design lock-in [27].

Agent-based simulation [15] might indicate the best path sequence to pursue given a desired level of fitness to be achieved. It could be used to evaluate potential outcomes stemming from an array of initial conditions and to assess the effects of random external influences along the design path. Agent-based simulation is useful when the results of each of a series of sequential events are determined by rules that trigger specific agent responses to the range of possible inputs to each event. The agents are active elements in the complex adaptive design and development system whose behavior is determined by the rule set [6].

Genetic algorithms [30] [6] present another approach for determining the best path to follow. Genetic algorithms may generate more effective alternate path directions, enable large jumps to new peaks on the landscape, and dynamically predict results. Systems engineers could use this approach to investigate the impact of using alternate or recombined technologies.

Each of these modeling approaches has unique features that contribute to their usefulness in analyzing the path dependence problem. System dynamics models specify deterministic responses during each sequential event by formulations that transform values of specific inputs into values of specific outputs. They are structure-based top-down macro-level continuous-flow models based on integral equations [31]. Agent based simulation models produce emergent responses at each sequential event, and those are enhanced by the ability of the model to change its rules in response to changing conditions. They are rule-based, bottom-up, micro-level, discrete flow models based on logic [31]. Both system dynamics and agent-based models can contain reinforcing and balancing loops that lead to non-linear trajectories. Genetic algorithms are biologically-based models designed to generate improved processes and configurations by stochastically generating changes in the artificial genetic structure of those processes or configurations at each sequential step, assessing if the change resulted in improvement or regression, retaining the changed process or configuration if the result was an improvement and repeating this approach until a desired level of fitness is attained. They are particularly useful for rapidly generating alternate configurations of developing products or systems and evaluating the fitness of each configuration using the process of hill climbing [14]. Thus, the choice of a model to analyze path dependence effects and implement effective strategies depends on the analytical objective and requires further in-depth research when assessing system affordability.

2.4 Quantifying and Measuring Affordability

A major part of the problem stated earlier in this paper is the lack of a consistent method for quantifying, measuring and assessing affordability. The affordability conjecture associated with this problem is that *relative* affordability or fitness of system variants can be measured and evaluated using the data envelopment analysis (DEA) model, where each decision making unit (DMU) is a variant of the same conversion process distinguished by different values of one or more key product fitness attributes. An associated conjecture is that the DEA model's solution space constitutes an NK fitness landscape.

This section describes DEA fundamentals, addresses the characterization of the DEA model's solution space (the production possibility set) as an NK fitness landscape, and suggests how the DEA model can be applied to evaluating product fitness. It addresses several questions raised by the conjectures stated in the previous paragraph and explores the potential use of DEA to measure and evaluate product fitness. Specifically, this section discusses the possibility that the DEA model solution space or the production possibility set can be represented in Altenberg's generalized NK fitness landscape. It advances the idea that the relative efficiency of products can be equated to relative fitness of products. This section also describes how key product fitness attributes are conceptually equivalent to the key input and output variables evaluated by the DEA model. Finally in this section, we describe how DEA already has been used to evaluate product fitness.

Data envelopment analysis is a process used to determine the relative efficiency of any conversion process[8], or more precisely, the relative efficiency of each instance of the same conversion process. Cooper, Seiford and Tone [32] describe DEA as a process that evaluates key input and output variables associated with decision making units (DMUs) to determine their technical efficiency. Each observed instance of a conversion process is termed a Decision Making Unit (DMU) and each DMU is evaluated as part of the aggregated collection of observed instances (DMUs) that depend on similar inputs and result in similar outputs. The analytic process is performed by selecting key input and output variables that affect the efficiency of all DMUs being evaluated, and using these variables in one of several available DEA models or identifying alternative formulations. DEA models use mathematical programming formulations to evaluate the efficiency of the set of outputs resulting from the conversion of a set of inputs for each DMU. The models compare the efficiency of each DMU with all other DMUs, and quantify this in terms of relative efficiency. The DEA models locate efficient DMUs on a production frontier of efficient DMUs, and locate inefficient DMUs inside that production frontier. The result of the analysis is an efficiency score, a performance target, a set of peers for each DMU, and a ranking of DMUs based on the relative efficiency score. Thus, data envelopment analysis is the process of determining and analyzing the efficiency of the set of DMUs on or enveloped by the production frontier [32].

Experimentation with the use of DEA to evaluate the fitness of R&D projects has indicated that DEA is a viable method for measuring and evaluating product fitness [33]. The DEA solution space can be envisioned as an n-dimensional landscape where the relative efficiencies of each DMU's input and output vectors are points on the surface of the landscape. Efficient DMUs are located at the peaks of the landscape and a surface passing through those peaks represents the frontier of the landscape. The DEA solution space dimensions are associated with the number of key variables evaluated for each DMU. This appears similar to Altenberg's generalized NK landscape [20], where N is the number of fitness attributes in the population being measured. Altenberg's landscape

[8] A conversion process as used here refers to an integrated set of activities designed for repeated use to transform a prescribed set of specific inputs (resources) into a prescribed set of specific outputs (resources).

does not use K but rather uses input vectors associated with output functions to reflect epistatic coupling. In the DEA solution space, the attributes are the key input and output variables that contribute to the efficiency of the DMU. Each DMU's input and output variables could be epistatically coupled, where one key input could affect more than one key output or a key output could be affected by more than one key input and thus contribute to the difference in relative efficiency of the DMUs based on the values of the input variables. Interestingly, specific DMUs on the frontier can be designated as peers for certain less efficient DMUs, and the less efficient ones made more efficient by adjusting the values of key input/output variables. This is similar to adjusting the values of the key variables on the NK landscape during the hill-climbing process to increase fitness. It is not yet clear if there is a correspondence between the DEA solution space and an NK landscape. The critical question is whether the DEA solution space can be used to evaluate the fitness of competing products or services, and thus their affordability [34].

The vacuum cleaner example introduced in Section 2 illustrates how DEA can be used to evaluate product fitness. Since it is difficult for a consumer to accurately rate the "goodness" of a significant number of vacuum cleaner features like those listed in Table 1, unless each vacuum is "home tested" for a period sufficient to accurately rate each feature, consumers can use rating services such as Consumer Reports to provide unbiased ratings of vacuum cleaners. Such data are not always at the level of detail shown in Table 1, but are often aggregated at a level that reflects a few key variables roughly associated with the affordability fitness functions. The data in Table 2, extracted from The March 2009 Consumer Reports [35], lists ratings for the top 25 upright vacuum cleaners.

DEA can use the data in Table 2 to measure the affordability of vacuum cleaners. The Consumer Reports' (CR) variables, shown in the second row of the table, represent key vacuum cleaner fitness function variables that represent the combined value of vacuum cleaner features that contribute to that variable. For example, some of those features listed in Table 1, under performance fitness functions, contribute to each of the performance fitness function variables in Table 2. The CR scores are not intuitive with respect to the individual variable rankings, so the variables are possibly weighted to arrive at those results. The weighting scheme, if any, was not provided.

Fitness Functions	Performance			Vitality		Adaptability		Resource Consumption		Consumer Reports score
Variables Top 25 Rated Brands	Carpet	Bare Floors	Tool Airflow	Noise	Emissions	Handling	Pet Hair	Weight	Price	
Hoover Windtunnel Turbopower	5	5	5	2	5	3	4	21	230	73
Kenmore Progressive	4	5	4	3	5	3	5	21	350	71
Hoover Tempo Widepath	5	5	4	3	5	3	5	16	80	70
Panasonic MC	3	5	5	3	5	2	5	21	550	68
Hoover WindTunnel Bagged	5	3	4	3	5	3	5	18	140	68
Kenmore Progressive 36932	4	5	4	3	5	3	5	22	350	68
Eureka Boss Smart Vac	4	5	3	3	5	2	5	20	170	68
Hoover WindTunnel Anniversary	5	4	3	3	5	3	5	21	160	67
Kirby Sentria	5	5	4	2	5	2	4	25	1350	67
Riccar SupraLite RSL3	4	5	0	2	5	3	5	9	350	66
Eureka Boss 40	5	3	4	3	5	2	5	24	140	65
Riccar Brilliance Premium	5	5	2	2	4	2	5	20	900	65
Dyson DC17 Absolute Animal	4	5	3	3	5	2	4	21	550	65
Panasonic AeroSlast	3	4	3	3	5	3	5	22	700	64
Hoover Winduinnel Bagless 5elf Propelled	5	5	3	3	3	2	4	25	250	63
Bissell Healthy Home	4	5	3	3	5	2	3	26	250	63
Riccar Supralite RSL4	5	5	0	2	5	3	5	9	470	63
Hoover Convertible	4	3	4	2	4	3	3	20	250	62
Dyson DC14 Complete Animal	3	5	4	3	5	3	3	19	400	62
Hoover Empower	4	4	3	3	5	4	5	17	100	62
Bissell Pet Hair Eraser	4	3	3	3	4	3	5	21	150	61
Eureka Altima	4	3	4	3	5	3	5	20	80	61
Bissell Momentum	4	4	4	3	5	3	4	18	120	61
Dyson DC07 All Floors Animal	3	5	4	2	5	2	2	16	80	60
Dyson DC18 Slim	3	5	3	3	5	3	3	19	300	60

Table 2. Consumer Reports Ratings of top 25 Upright Vacuum Cleaners

Table 3 shows the results of the data envelopment analysis of all 38 products listed in the March 2009 Consumer Reports upright vacuum cleaner ratings. The input variables used in the DEA model were the seven variables in Table 2 associated with the performance, vitality and adaptability fitness functions. The output variables were price and weight. The Charnes, Cooper, Rhodes input minimizing DEA model was used [5] because constant returns to scale were assumed and the objective was to reduce input values characterized in the resource consumption fitness function. Table 3 shows only the top 25, as rated by data envelopment analysis efficiency. Fifteen products appear on both top 25 lists – those highlighted in Table 3. Sixty percent of the products appear in both top 25 lists as well as both top ten lists. Since the data envelopment analysis is unbiased and the outcome of the analysis is relative fitness, [5] consumers can narrow their alternatives to a few competing products. Added techniques, such as cross efficiency evaluation, are available to further rank the efficient products and further narrow the alternatives. [34] While this analysis shows how DEA might be used to evaluate product fitness, and thus affordability, only the DEA model applied weights to the variables. So the scores do not reflect the weights used by CR in the consumer ratings to produce those scores. If those weights were known, the comparison between DEA ranks and CR ranks would have been different. In this case, the correlation coefficient between the DEA scores and CR scores is 0.02. Nevertheless, DEA appears to be a viable method for ranking product fitness and could very well produce better results than the CR ranking.

Product	DEA Score	CR Score	Product	DEA Score	CR Score
Bissell Lift-off Revolution Turbo	1	57	Hoover Windtunnel Turbopower	0.73	73
Dyson DC07 All Floors Animal	1	60	Kenmore Progressive	0.69	71
Dyson DC24 Ball All Floors	1	57	Hoover Tempo Widepath	1	70
Eureka Altima	1	61	Hoover WindTunnel Bagged	0.87	68
Hoover Empower	1	62	Eureka Boss Smart Vac	0.77	68
Hoover Fold Away Widepath	1	48	Hoover WindTunnel Anniversary	0.74	67
Hoover Tempo Widepath	1	70	Riccar SupraLite RSL3	1	66
Riccar SupraLite RSL3	1	66	Riccar Supralite RSL4	1	63
Riccar Supralite RSL4	1	63	Hoover Empower	1	62
Panasonic Performance Plus Platinum	0.93	58	Dyson DC14 Complete Animal	0.69	62
Oreck XL Deluxe	0.90	51	Eureka Altima	1	61
Hoover WindTunnel Bagged	0.87	68	Bissell Momentum	0.87	61
Bissell Momentum	0.87	61	Bissell Pet Hair Eraser	0.74	61
Hoover Elite Rewind	0.84	50	Dyson DC07 All Floors Animal	1	60
Kenmore Stylite	0.80	50	Dyson DC18 Slim	0.72	60
Kenmore Premalite	0.78	56	Panasonic Performance Plus Platinum	0.93	58
Eureka Boss Smart Vac	0.77	68	Bissell Lift-off Revolution Turbo	1	57
Bissell Pet Hair Eraser	0.74	61	Dyson DC24 Ball All Floors	1	57
Hoover WindTunnel Anniversary	0.74	67	Kenmore Premalite	0.78	56
Hoover Windtunnel Turbopower	0.73	73	Eureka Capture	0.72	54
Dyson DC18 Slim	0.72	60	Oreck XL Deluxe	0.90	51
Eureka Capture	0.72	54	Hoover Elite Rewind	0.84	50
Kenmore Progressive	0.69	71	Kenmore Stylite	0.8	50
Dyson DC14 Complete Animal	0.69	62	Hoover Fold Away Widepath	1	48
Koblenz	0.67	39	Koblenz	0.67	39

Table 3. Results of Data Envelopment Analysis of Product Efficiency

2.5. Conclusions

Consumers throughout the value chain should be able to benefit from affordable products and services – purchases that perform at the level of quality required by the consumer, perform at that level whenever required during the useful life of that product or service, and do so with minimum consumption of material and financial resources. But despite over eight years of affordability science research, we lack a systematic approach to developing affordable systems; and we lack a consistent method for quantifying, measuring and assessing affordability that accommodates a system of non-linear input and output variables with various measurement units. This happened because, despite significant efforts to characterize, quantify and measure affordability, that objective was never fully achieved.

This paper addresses these shortcomings by considering affordability as fitness of technological systems. It suggests that the characteristics and behaviors of natural systems can be used to provide insight into methods for developing desired characteristics and behaviors of technological systems that will make them affordable. The paper describes four fitness functions – performance, vitality, adaptability and resource conservation – functions that provide clues to developers, designers, engineers and manufacturers regarding product or service attributes that will render them more affordable. The paper also provides potential methods and modeling techniques for system designers and engineers to develop affordable products by analyzing the potential effects of path dependence on fitness attributes. We also demonstrate a possible effective method for measuring product fitness by using data envelopment analysis to evaluate the relative efficiency of key fitness attributes associated with affordability fitness functions.

The broad impact of this research will be the ability to reap the benefits of more affordable products, both as an end customer, and as a producer who transforms materials received as a customer into products for consumption by customers in the value chain. The by-products should be better performing products with longer, uninterrupted service life that require fewer resources to produce and use.

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3. Path Dependence in Systems Engineering: Affordability Implications

Abstract

During a system design evolution, the specific design outcome is determined by that set of design search paths followed – it is path dependent. Dynamic mechanisms create, dictate and maintain path dependence. Initial conditions define the start and direction of a path. During subsequent design steps, positive feedback influences the designer to continue on that path. Frequently, the design gets “locked-in” due to unforeseen external conditions that eliminate other practical alternatives. Path dependence can produce positive or negative effects. Positive feedback could accelerate achievement of the best design. But continuing along a path of positive feedbacks could cause the system designer to miss better solutions. This paper describes underlying mechanisms that create, dictate and maintain path dependence, discusses the effects of path dependence on system design and system affordability, and suggests actions to address its effects. System dynamics models of path dependence during concept design, preliminary design and detailed design depict the effects of path dependence on technology selection, cost, schedule, and lock-in, reinforcing the impact of path dependence and results of actions to address that impact. Effects of alpha and beta test errors, lock-in, and intentional excursions from the path are demonstrated.

Key words: affordability, path dependence, initial conditions, positive feedback, lock-in, systems design

3.1 Introduction and Context

Consumers are constantly pursuing better performing, more useful, higher quality products and services at a reasonable price. In other words, consumers continually seek new, affordable products and services, where affordability is defined as the characteristic of a product or service that enables it to perform at the level of quality demanded by the consumer, is available to perform whenever the consumer needs the use of the product or service, and can be procured and operated for a reasonable cost [1]. Although some new products may be so unique that they create their own market, many new, affordable products and services appear as variants or composites of prior products and services. Transformations from one product or service generation to the next can range from minor changes to major innovations. This transformation process is termed technological evolution.

Technological evolution results from the interaction of consumers, engineers and producers that are the active agents in the overall process, and from the resulting flow of resources and information between these agents. In response to consumer feedback, engineers and producers use some set of performance rules to exchange resources and to produce new or improved products and services. The agents interact in dynamic sequences, patterns, and cycles of resource and information flow, sometimes producing startling results during technological evolution.

Kauffman [2] describes these dynamic interactions and outcomes in *At Home in the Universe*. He points out that technological evolution, like biological evolution, features processes that operate in a co-evolutionary, co-adaptive environment,[9][3] where networks of agents evolving in interacting systems can have a significant impact on the change in a particular product or service. While many products and services are slightly altered to adapt to a gradually changing environment, innovative new products and services also rapidly emerge to respond to significant shifts in consumer requirements. The nature of the transformations resulting from such agent-based interactions indicates that

[9] Coevolution is a process of adaptive moves by interacting systems, where each system affects the fitness of the other, and each system's fitness depends on the other system's fitness. During coevolution, each interacting system co-adapts to the effects of the other system by altering its existing attributes or generating new attributes.

technological evolution operates as a complex adaptive system seeking to increase system fitness.

John Holland [4] describes complex adaptive systems as systems composed of interacting agents that adapt by changing their strategies as they accumulate experience. In biological systems, adaptation enables an organism to achieve greater environmental fitness. Similarly, in technological systems, adaptation enables the system to effectively respond to changes in the operational environment. As suggested in Chapter Two, complex adaptive systems provide a robust dynamic representation of fitness that can be applied to product affordability. So technological system fitness can be described as product or service affordability, and affordability can be modeled as system fitness [5].

One of the key elements in developing and producing new, affordable products and services is the systems engineering process. An underlying phenomenon of the systems engineering process, one that affects product or service affordability, is a characteristic of complex adaptive systems called path dependence. Path dependence is a sequential system development characteristic where initial conditions, random events, and positive feedback all conspire to dictate the path taken to complete the development process [6]. Path dependence is evident in economic, political and biological development, and particularly in technological development. Since the role of systems engineers is to bring systems into existence through the technological development process [7], systems engineers need to recognize path dependence, its elements and its consequences.

The objectives of this paper and the research described herein is to characterize path dependence in terms that system developers, designers, engineers, and decision-makers recognize and understand; and to describe approaches that can enhance the positive aspects of path dependence, and overcome or reduce the negative aspects. The paper begins with the background of path dependence to provide a point of departure for a further description of path dependence. Next, it explains a conceptual model of path dependence by describing the dynamic sequence of events that can take place during the development of a technological system. Following that, the paper describes elements of the systems engineering design process that affect path dependence and shows how path dependence can influence the outcomes of that design process. It concludes with suggestions for overcoming the negative effects of path dependence and for taking advantage of the positive effects.

Although the literature has associated path dependence with technological development, it has not explored the impact of path dependence on the systems engineering design process in detail. This paper describes the impact of path dependence on each systems engineering design phase and analyzes the influence of each element of conceptual, preliminary and detailed design on path dependence. In addition, it provides the first systems dynamic model, which, though elementary, provides a basis for significantly more detailed modeling.

This paper explains undesirable design outcomes such as lock-in to lower quality designs and tendencies to continue on a less productive design path due to successive positive feedback that occur as a consequence of path dependence. The paper also offers systems engineering policies and strategies to take advantage of positive effects of path dependence and to recognize and avoid negative effects. Since path dependence is a complexity sciences phenomenon, this paper contributes new information to the complexity sciences literature.

3.1.1 Background

The literature addresses path dependence and its effects across many areas involving system development and growth. Sterman [6] devotes an entire chapter of his textbook *Business Dynamics* to path dependence. He defines path dependence as a system behavior pattern where small, random events in a system dominated by positive feedback determine the ultimate system state. Sterman [6] illustrates the process and explains the effects of path dependence, such as lock-in, associated with technology, business, and economics.

O'Sullivan [8] claims that path dependence and positive feedback are useful metaphors generated by complexity science to describe system dynamics. He explains that path dependence defines a current system's state as a function of prior states reinforced by positive feedback. Levin [9] reinforces that explanation by observing that all complex adaptive systems reflect path dependence during their development. His description of path dependence as a consequence of nonlinearity because of changing interactions within systems, as they evolve, reinforces Sterman's observation that non-linear functions should be used in modeling path dependence since linear models are restrictive with unrealistic assumptions[6].

Arthur [10], a noted economist and complexity scientist, relates the dynamic effects of path dependence in the economy, pointing out that positive feedback magnifies the impact of small changes and often influences increasing economic returns. He observes that high-technology, knowledge-based products and systems generally enjoy increasing economic returns due to path dependence, and while resource intensive systems are not strongly affected by path dependence, they are usually constrained to diminishing economic returns. Arthur also observes that path dependence can produce some less desirable results such as lower competition; higher, unstable prices; fewer choices; and ultimately lock-in to a specific product or process. Arthur describes lock-in as the selection of one competing technology based on historical small events beyond the knowledge or control of a decision maker. This often begins as a random choice of that technology and a subsequent succession of those small events that increase the dominance of that technology. When support of and for the other competing technologies fades (and sometimes disappears), the decision maker is locked-in to the dominant technology.

The literature specifically addresses path dependence as it relates to technological evolution and development. Gether's [11] doctoral dissertation discusses technology choices under conditions of path dependence, feedback and nonlinearity. She points out that information obtained through modeling technological development must account for path dependence that could lock-in sub-optimal technology choices. She describes lock-in as the selection of a dominant design where the cost of switching to another design is prohibitive. Metapati [12] asserts that the rate of technical innovation reflects the influence of path dependence. He traces the innovative development of the microprocessor and the effect path dependence had on its development. Wang [13] discusses the impact of path dependency on designing flexibility into physical systems. His doctoral dissertation includes methods to simplify the very complicated path dependence problem encountered while selecting options for systems design such as various configurations of a power converter.

Frenken [14] observes that interdependence among components in complex technological systems constrain the adaptive capabilities of those systems, which in turn constrains the paths available for the system to evolve. During system development, many changes to existing configurations may benefit part of the system but have negative consequences for the overall system – only a few changes usually benefit the entire system. The fact that these few successful changes depend on the precise configuration of the system indicates that such complex systems are very path dependent.

Thus, the literature indicates that path dependence is found in virtually every developing system. Path dependence can produce beneficial results, but also it can create problems by limiting the perceived options available for creating new system designs or improving existing designs. This reinforces the idea that system designers, as well as systems engineers, need to recognize path dependence, understand the involvement of path dependence in technological evolution and development, take advantage of the positive results of path dependence, and take action to avoid its undesirable consequences. But the literature does not focus on specific dynamics of path dependence during the systems engineering design process, nor does it suggest approaches to avoid undesirable effects. The remainder of this paper remedies this gap in the literature by explaining the dynamics of path dependence that causes the behavior described by Frenken; exploring the systems engineering design process to pinpoint where system developers and decision-makers need to influence and assess path dependence; describing how a system dynamics model can be used to assess or predict the impact of path dependence on system development outcomes; and suggesting some methods for inducing or taking advantage of positive effects or avoiding negative effects of path dependence.

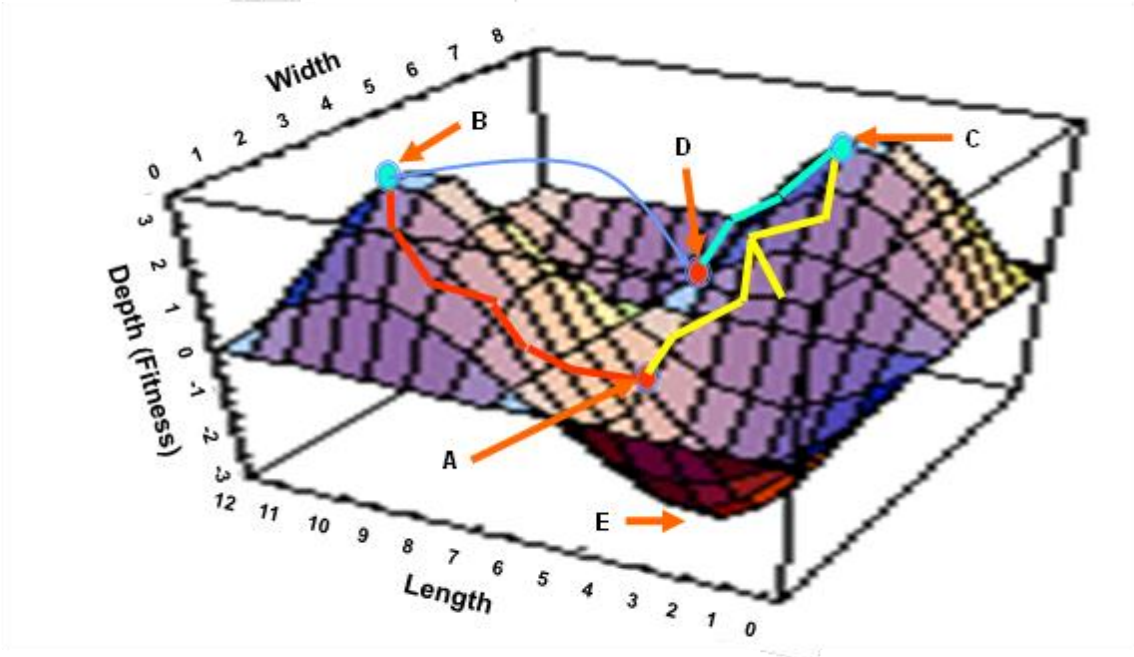
3.2 The Conceptual Path Dependence Model

Path dependence can be modeled by incorporating three complexity science-based concepts that help to explain path dependence and its effects. The first concept is that of system fitness. Webster [15] defines fitness as environmental adaptability so as to be capable of surviving, and describes fitness as suitability or special readiness for a particular use. In biological evolution, fitness reflects system survivability – the higher the fitness, the more likely the system will survive. It follows that system fitness during technological evolution reflects a system's suitability to fulfill its intended use – the higher the fitness, the more likely the system will effectively fulfill its purpose.

The literature [6, 16, 17], the experience of many systems developers and engineers, and one's intuition indicate that technological evolution follows a distinct path – a sequence of steps, each of which depends on the prior step. The relationship between this path dependence and system fitness can best be understood through the use of the second complexity science-based concept: that of fitness landscapes[10]. A systems engineer or designer might view technological evolution on such a fitness landscape, where increased fitness is achieved by metaphorically climbing to a higher point on the landscape.

Kauffman [2] suggests that fitness of technological systems can best be modeled on a correlated landscape, where clusters of somewhat rugged peaks with varying altitudes represent different levels of fitness – the higher the peak, the greater the fitness. Figure 2 illustrates such a correlated landscape. Before the climb commences, the systems designer chooses, often randomly, that starting point (A) and design path (red) which appear to offer the best chance of improving design fitness. The designer continues on that path as long as positive feedback indicates the correct design choice was made. Chapter 4 suggests methods for measuring fitness and thus receiving feedback during the systems engineering design process. If negative feedback indicates that progress is downhill, the designer looks for and chooses a different path. If the designer encounters a design obstacle that dictates a change in direction or perhaps a retreat (metaphorically a cliff or ravine), the designer also takes another path. If a chance occurrence threatens the design (metaphorically falling rocks), the designer may work around that threat or change direction. Note that the higher the designer climbs, the fewer the number of available upward paths. And, when a local peak is reached (B) there are no remaining upward paths, so at least a local optimum point is attained.

[10] A fitness landscape is a multi-dimensional, conceptual solution space where each important variable associated with objects being assessed for fitness defines a dimension of the landscape. The location of a radial vector of the fitness variables that emanates from the origin of the landscape defines an object's position on the landscape. The landscape contains one or more hills and valleys defined by the location of all object vectors. The fittest object is located on the highest local hill and other less fit objects located on the hillsides or in the valleys. As the value of an object's variables change, the vector's location will change. Attempts to improve the fitness of an object on a fitness landscape are referred to as hill-climbing.



Adapted from Path Dependence Briefing to the Office of Naval Research [18]

Figure 3. **Path Dependence in System Design on a Fitness Landscape**

Hill climbing is complete when the design reaches the desired level of system fitness. However, if the desired system fitness is not achieved at that local peak, the designer must decide whether to accept the level of fitness achieved or look for a higher hill. If it is too expensive to pursue another path, the design may be locked-in at this point. Or, if available technology will not support searching in other directions, the designer may be forced to lock-in to this design. However, if further search is feasible, the designer might retrace the prior path and search for a new path (yellow) to a higher hill and begin the upward climb to its peak (C). If the nearest higher hill is quite far though still visible, the designer may find a way (perhaps a new technology) to completely escape the path that led to the lower hill and jump to the base of that higher hill (D), a technique known as long-jump adaption. [2] The designer may be able to climb a new path (blue) more rapidly to the peak of that hill and more easily achieve the desired fitness based on the experiences encountered on the original path.

The complexity science-based concept of coevolution must be considered in this path dependence model. Kauffman [2, 3] describes coevolution as the interaction between systems as they simultaneously evolve. The development of each technological system affects the other as they coevolve. Kauffman points out that the shape of the fitness landscape changes as systems coevolve – available paths and local peaks shift causing changes in the points of highest system fitness and the ways to approach these points. Just when the system designer is about to reach a desired fitness level, a search along new or prior paths may be required due to coevolution and the shifting fitness landscape. The new search might yield better fitness if higher peaks are attainable, or produce lower fitness because the coevolving system reduced the altitude of available peaks on the fitness landscape. The worst case could be lock-in to a low fitness design because the changing landscape has eliminated some paths, and the designer is trapped on a low fitness peak or in a low fitness basin (E) from which there is no escape.

So, during technological evolution, the specific outcome is dictated by the set of search paths followed – it is path dependent. And obviously, the shortest overall path length should be the most cost effective and efficient if the desired level of fitness is achieved. If the system designer avoids obstacles and random diversions, copes with the possible effects of coevolution, and chooses the best set of search directions, design efficiency and effectiveness can be achieved along with high system fitness. But in the world of systems engineering and system design, metrics and mechanisms for providing feedback dictate the level and direction of path dependence. This is true during conceptual design, preliminary design and detailed design: the three phases of systems engineering that precede system production, operation and phase-out [7].

3.3 Impact of Path Dependence on System Design

The literature suggests that four conditions dictate the technological development path: the initial starting point and direction, small random events that occur during the technological evolution, coevolution of interacting systems, and positive feedback. Since the systems design process almost always features these four conditions, path dependence can be expected to have a significant effect on the design throughout the process.

3.3.1 Conceptual Design

Conceptual design is the first phase in the technological evolution process. System requirements are derived from customer needs, and a concept of operations is developed to meet these requirements. This concept of operations describes primary mission activities along with associated maintenance and support activities. System level measures of effectiveness (MOEs) are established and quantified to evaluate how well each design alternative meets established requirements. A Systems Engineering Management Plan (SEMP) provides overall guidance and a Test and Evaluation Master Plan (TEMP) establishes tasks and schedules for performing design analysis and testing. Each design concept is evaluated as specified in the TEMP. At the end of the phase, the feasibility of each concept is assessed and the fittest concept is selected, established as a functional baseline, and documented in the top-level system specification [7, 19].

Critical steps in the preliminary design sequence dictate the technological development path. Defining system requirements is very important, since measuring the wrong performance parameter is likely to place the design on the wrong path. Establishing legitimate, unambiguous system level MOEs is the most critical step, since design fitness will be evaluated using these MOEs, and they will determine whether feedback is positive or negative. Another important step is establishing support activities associated with mission activities. This frequently involves tradeoffs, and that implies that mission and support activities might coevolve during the concept design evolution and system fitness might vary as the landscape is reshaped.

Path dependence can affect the conceptual design phase in several ways. A sub-optimal alternative could be chosen and a better alternative overlooked if positive feedback based on inappropriate requirements, poor MOEs, or coevolution indicates the selected alternative presented as the best design path. Similarly, the systems engineer could conclude that the entire concept is or is not feasible based on the same type of feedback errors such as erroneous performance data that indicate a similar operational system would or would not be an appropriate exemplar for the system being designed.

3.3.2 Preliminary Design

Preliminary design begins with a functional analysis based on the system specification, and that leads to development of functional performance requirements. These requirements specifically address functional, performance and design needs. Performance and design factors, along with effectiveness requirements, are allocated to the specific functions to be performed. Effectiveness requirements are defined in terms of system level MOEs, physical or functional measures of performance (MOPs), and technical performance measures (TPMs). These performance measures are used in simulations and component or breadboard tests to evaluate functional design, judge alternative approaches and select the best system alternative. Life cycle cost estimates are developed in parallel with performance parameters. An updated SEMP and TEMP provide guidance, tasks, schedules and test methods for performing these evaluations. At phase end, the selected alternative becomes the allocated baseline shown in preliminary design documents such as development, process, product, and material specifications. [7, 19]

Critical steps in the preliminary design sequence have more impact on the technological design path than in the conceptual design phase. It is important for functional requirements to reflect the design concept and "voice of the customer," since variances likely will start the design on the wrong path. It is very important to establish clear, unambiguous performance and design requirements, for they become the basis for establishing system level, functional and technical performance measures. Measuring the wrong parameters will surely put the design on the wrong path. The most critical step is quantifying performance measurements. If MOEs, MOPs or TPMs do not accurately reflect performance goals, tradeoff decisions may be faulted; substandard performance accepted; or superior performance rejected. Such results could be particularly serious when evaluating Key Performance Parameters. It is important to update the TEMP and provide current details regarding test requirements and methods. Setting cost targets could also be important in avoiding early commitment to high detailed design and production phase costs.

In the preliminary design phase, path dependence resulting from positive feedback during simulation and testing can positively or negatively influence design decisions. If MOEs, simulations and test methods are effective, design alternatives are likely to be accurately assessed and the correct design path indicated. And a succession of accurate positive feedbacks can more quickly and cost-effectively produce the highest fitness design alternative. However, if design assessments and tradeoffs are faulty, the wrong design path may be indicated – the designer may continue on a low fitness design path or erroneously take a new low fitness path. Once a new path is chosen, successive positive feedbacks may mask the design’s ultimate low fitness until late in the preliminary design phase or even in the detailed design phase. At that point, it may be too expensive to search for and find a higher fitness path and the design may essentially be locked-in. While lock-in to the highest fitness design can be beneficial, unforeseen events such as unavailability of critical materials or failure to develop a new, key technology could force the systems engineer to lock into a lower fitness alternative.

3.3.3 Detailed Design

Detailed design is focused on design of the specific system or product selected during preliminary design. Allocated baseline documents provide the basis for developing and allocating design requirements to all system components, subassemblies, assemblies, subsystems and software, and for developing interface design requirements for integrating these configuration items. Designs reflecting these requirements are developed and implemented and a system prototype is created with which to evaluate system structure, performance and overall fitness. The TEMP is updated for this phase and specifies intensive testing at every design level. The general sequence of design, build, test and integrate is repeated throughout the phase to assess fitness at each level. Process, product and material specifications are updated throughout the phase with changes controlled through a configuration control board. Cost estimates are reviewed and updated and variances from prior estimates noted. The phase ends with a product baseline documented in the latest updates of the process, product and material specifications [7, 19].

Critical steps affecting the technological development path during detailed design are heavily weighted toward design testing. One critical step is conversion of system functional, physical and design requirements into clear, traceable configuration item requirements. The next step is developing physical and functional designs that effectively convert these requirements into real hardware and software that accomplish their purpose. Perhaps the most critical step is establishing test methods and metrics that truly measure the fitness of each configuration item, which means that the metrics must reflect the allocation of previously specified performance measures down to the configuration item level. The TEMP must be updated to reflect these methods and metrics and the sequence in which they are to be applied. It is also important to establish cost targets for the fabrication or development of configuration items.

In the detailed design phase, the technological evolution path contains many more segments. Each component represents a starting point that features an initial condition and path direction. Designers must make that choice based on the design specification, and often rely on prior similar designs, previous experience, or shared knowledge to establish initial conditions and path direction. So the starting point and direction for a component development path might be path dependent. Each in-process and completed item test presents an opportunity to evaluate the fitness of a configuration item. If metrics and test methods are effective, the design is likely to be accurately assessed and the correct design path indicated. If metrics and/or test methods are ineffective, the design may be erroneously accepted or rejected. This error will roll up with integration at each level and continued positive feedback will compound the error until it is finally detected or mitigated. Mitigation might be accidental and never perceived, but if the error is detected far up the technological development path, it may be difficult and costly to trace the error to its source and even more costly and time consuming to change the path. Integration introduces coevolutionary effects that may amplify already high fitness or may interfere and reduce fitness. The further the design and integration progresses, the more vulnerable the design path becomes to lock-in. Undesirable lock-in might occur if negative feedback dictates a new path that is prohibitively expensive, or a technology that is not sufficiently developed or supported. However, lock-in due to overwhelming, high fidelity, positive feedback is desirable since the right technological path was selected.

3.4. Systems Design Model

As stated above, the technological development path is a function of the initial starting point and direction, small random events that occur during the technological evolution, coevolution of interacting systems, and positive feedback.

$$\boldsymbol{Development\ path} = \boldsymbol{f}(\boldsymbol{initial\ conditions}, \boldsymbol{random\ events}, \boldsymbol{coevolution}, \boldsymbol{feedback})$$

A system dynamics model of path dependence during systems design was structured to quantitatively illustrate these effects. The products modeled for this phase are technology designs, which refer to technology development component, subassembly and assembly designs, including brass-board and advanced development units associated with the key functions and concepts evaluated in the concept development phase. The model accommodates two technologies, and, during each period, generates and assigns a technology design to one of the two technologies. The total number of technology designs to be developed during the model run is an exogenous variable. Figure 3 is a simplified version of the model showing key variables and relationships for generating designs for one of the two technologies.

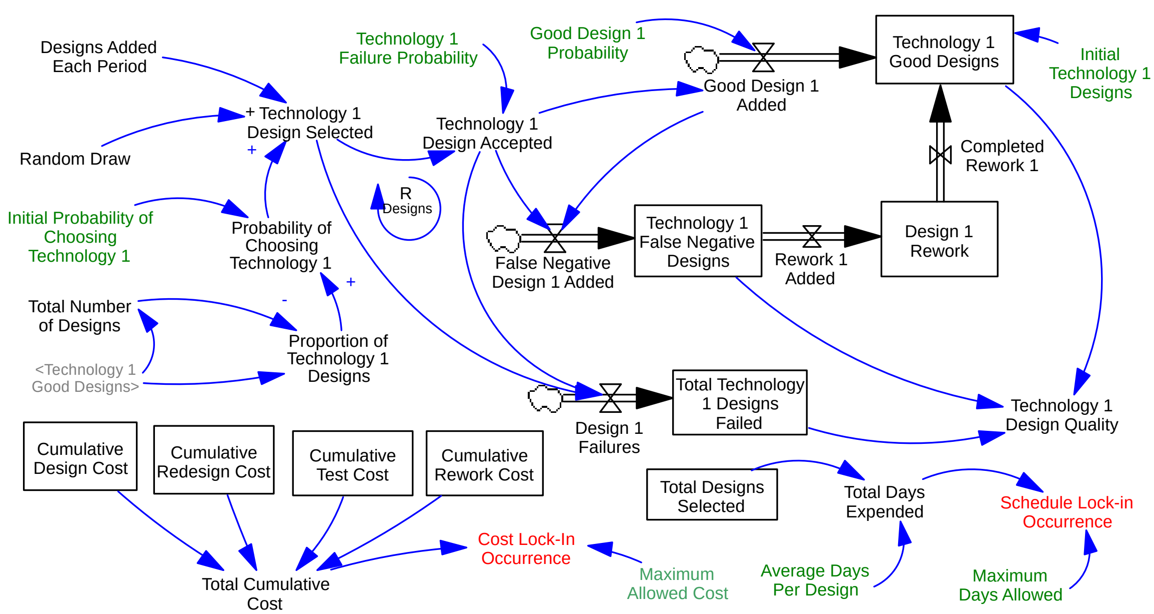


Figure 4. Causal Loop Diagram of Key Variables Used to Model Path Dependence in Systems Design

During each model period, the model generates and assigns a design to one of the two technologies. The assignment is made based on the probability of selecting a technology during each period. The non-linear Polya process is used to generate the probabilities of selection during each successive period. This model is adapted from Sterman's non-linear Polya process formulation, which generates path dependent results [6]. The degree of path dependence is regulated by an exogenous "sensitivity to proportion" variable (not shown in Figure 2). The probability of selecting a specific technology design is based on the ratio of the previous selection of that technology to the total instances of technology selection. Generating a random uniform variable and comparing it to the probability of selection determines which technology design is selected. The initial technology is based on the initial "random draw" variable (*initial condition*). The model operates as follows. The "initial probability of selecting technology 1" variable is an exogenous variable that allows the user to define that initial condition for the "probability of choosing technology 1" variable. The "initial technology 1 designs" variable is an exogenous variable that defines the initial value of the "technology 1 good designs" stock. That value is usually set at one for each technology, so if there are two technologies being modeled, the initial "proportion of technology 1 designs" will be 0.5. The "probability of choosing technology 1" variable during each succeeding period is a function of the "proportion of technology 1 designs" previously chosen.

The design reinforcing loop begins with the "probability of choosing technology 1" as an input to the "technology 1 design selected" variable. Sterman's formulation in the "technology 1 design selected" variable features random perturbations generated by an exponential function in order to make the probability of choosing that technology non-linear. If that technology is selected, the design undergoes inspection and/or test with the result determined by the "technology 1 design accepted" variable. The probability of passing a design inspection and/or test is the "technology 1 failure probability" exogenous variable. Inspection and/or test are treated as a single event during each period in the model run. A random uniform variable is generated and compared to the probability of passing the inspection or test to determine if the design passed or failed. If the design is accepted, there is a random probability that it was a false negative[11] (*random event*), which is determined by the “good design 1 probability” exogenous variable. Another random uniform variable is generated and compared to the “good design 1 probability” of not being a false negative. If it is a good design, it is added to the “technology 1 good designs” stock. If it is a false negative, it is added to the “technology 1 false negative designs” stock, where it will await discovery as an unacceptable design then be added to the “design 1 rework” and placed in the “technology 1 good designs” stock after rework is completed. The addition of a design to the ““technology 1 good designs” stock increases the “proportion of technology 1 designs” variable, thus increasing the “probability of choosing technology 1” variable (*positive feedback*). If the result determined by the “technology 1 design accepted” variable is design failure, the “proportion of technology 1 designs” does not change (*negative feedback*). If the feedback is positive, a new design is added to one of the technologies. If the feedback is negative, the failed design is (nominally) re-entered into the process thus adding to the total number of designs to be processed.

A rare external event called an extinction event (caused by *coevolution*) can also be randomly generated, and the result is to restart the entire technology design process. An extinction event might result from non-availability of critical resources or the decision to execute a long jump to an entirely new technology. The probability and period of occurrence of an extinction event are controlled by exogenous variables. If a rare extinction event is generated, the “extinction event” variable removes all designs in the “technology 1 good designs” stock. Feedback from the “technology 1 good designs” stock to the “total number of designs” variable and the “designs added each period” causes the model to start the process from the beginning.

The model accumulates costs and schedule days required to complete the system design. Separate cost data are captured for technology design, for inspection and/or test, for redesign of failed units, and for rework. The cost accrued in each period of the model is generated by multiplying exogenous maximum cost variables for design, test, rework or

[11] A false negative, also known as a Type II error, is a condition where a design is accepted when, in fact, it is deficient and should have been rejected.

redesign by exogenous table values that define the percentage of maximum cost that applies to that period of the model run. The resulting costs are accrued in cumulative cost stocks. Schedule days expended to complete the design process are determined by multiplying an exogenous average days per design variable by a total designs selected stock. The model also reflects potential lock-in to designs by comparing maximum allowed days to total days expended and comparing maximum allowed costs to total cumulative cost. When the cost or schedule lock-in occurrence variable equals one, that point has been reached, though the model will continue to run until all designs are completed.

The model run is completed when the number of completed designs ("total number of designs" variable) equals the total number of designs required ("total designs" variable). To evaluate the impact of initial conditions on path dependence, initiate another run after changing the exogenous "random seed input" variable while retaining the same values of other exogenous variables. Assess the effect of feedback on path dependence by changing the exogenous "technology failure probability" variables' values while holding other exogenous variables constant. Evaluating the impact of random events is accomplished by changing exogenous "good design probability" variables' values with other exogenous variables held constant. Coevolution effects on path dependence can be modeled using different exogenous extinction variables while retaining other exogenous variable values.

The parameter values for the model runs are found in appendix A. The impact of path dependence on technology designs is reflected in Figure 4. This graph of 3 system dynamics model runs shows the rapid convergence to one technological path during systems design. It also shows varying numbers of designs despite holding selection probabilities, failure probabilities, and false negative probabilities constant. The only difference is the random number seed used to initiate the model runs.

Figure 4a. Initial Conditions

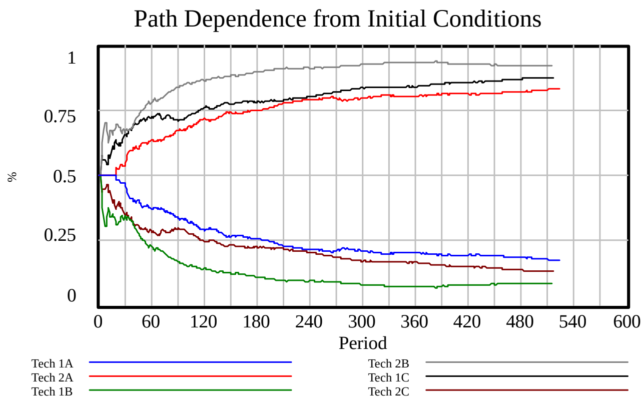


Figure 4b. Positive Feedback

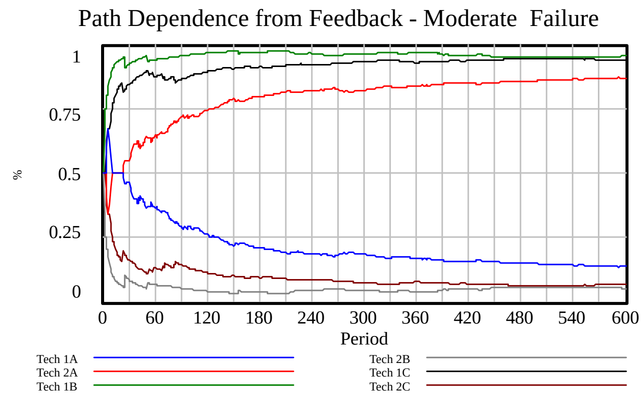


Figure 4c. Random Events

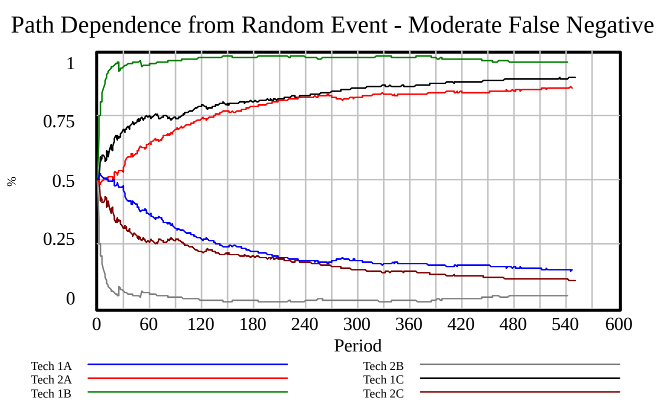


Figure 4d. Coevolution

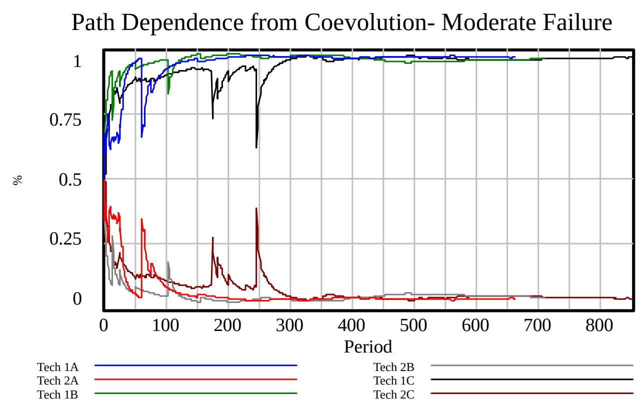


Figure 4e. Negative Feedback

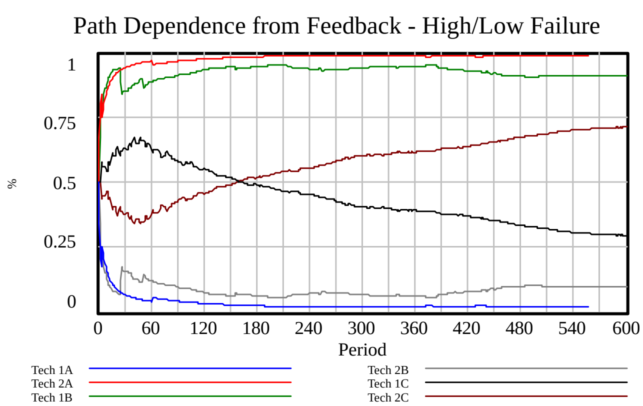


Figure 4f. One Technology Coevolution

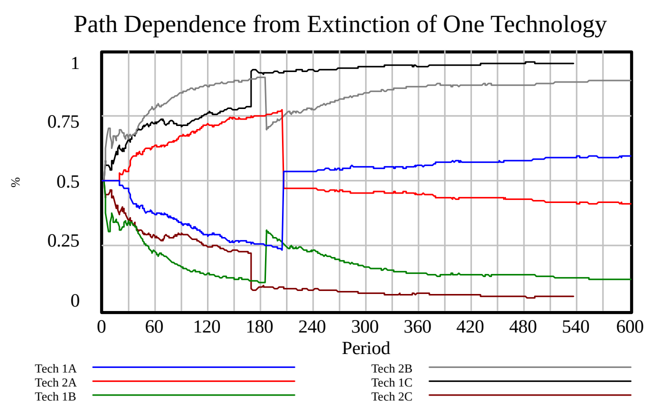


Figure 5. Path Dependence of three sets of technology designs with identical probabilities of selection and failure but different random number seeds

Figure 4a shows that the impact of initial conditions might cause a dominant technology to develop quickly, as in technologies 1B and 2B, or to not diverge from the other technology until later, as in technologies 1A and 2A. Note that technology 1 dominates in one case and technology 2 dominates in the other two cases, which means that the initial random seed (initial condition) changed random draws that affected technology dominance despite the same probabilities of selection, acceptance and good design. Figure 4b reveals that feedback from moderate failures changes technology 1B to a dominant technology and accelerates the dominance of technologies 1B and 1C. Figure 4c is similar to 4a; except technology 1B has become dominant as in Figure 4b and all technologies accelerate path dependence at least somewhat. All three figures reflect fluctuations that are caused by test failures of false negative events, none of which affect a technology's relative dominance or weakness. Figure 4d shows the effects of environmental influences with which the technologies coevolve. In this case, two extinction events (perhaps a total failure of a design approach and later a supplier going out of business) cause restarts of the design process, but no change in the dominant technologies, since rework designs are still in process thus increasing the probability of choosing the dominant technology. Figure 4e reflects results of one technology having a higher failure rate than the other. Technology crossover is affected by the number of good designs in the good design stock. Technology 1 dominated initially during Run C, but the high failure rate caused increased acceptance of technology 2 designs, and positive technology 2 feedback reinforced the upward trend of the technology 2 path. In Runs A and B, technology 2 quickly dominated from initiation with less failures. This is shown graphically in Appendix A, Figure 13. Figure 4f also displays technology crossover, this time as a result of one technology suffering a 75% extinction event. However the result is counterintuitive – the weak technology crosses over and becomes the stronger one, though it is not completely dominant. Even though technology 2 dominated good designs initially during Run A, the technology 1 extinction event was sufficient to change the proportion of each technology designs to slightly favor technology 1 and cause that technology to subsequently produce more designs than technology 2. The other technologies were less affected and no crossover occurred, though Run C showed similar effects as in Run A. This is shown graphically in Appendix

A, Figure 24. In any case, positive feedback at each step of the design process will cause the dominant technology to continue along its path. Additional figures with path dependence results are displayed in Appendix A-1.

This model can be applied to real applications by entering the appropriate parameter values for exogenous variables such as probability of passing, percent of false negative test results, average rework delay, average time to perform rework, cost table, schedule table, maximum costs and schedules for design, redesign, test and inspection, rework, maximum allowed days, maximum allowed schedule, and total designs required.

3.5. Strategies and Techniques to Address Path Dependence

Systems engineers and designers need to employ strategies that take advantage of path dependence and offset potential shortcomings. The following interventions, derived from previously described descriptions of the impact of path dependence, provide a framework for more detailed strategies in the context of this paper. The listed strategies emerged from the path dependence research, the systems engineering literature and the preceding path dependence discussions. They include the application of the system dynamics model illustrated above using Sterman's system dynamics formulations [6].

Model the complete path for a design phase to identify critical variables in the design path and assess the impact of positive and negative feedbacks associated with those and other variables. For example, setting the average test failure rate lower than expected during one model run and higher than expected during another model run could indicate downstream points where lock-in might occur.

1. Establish clear, measurable requirements and high fidelity metrics for evaluating system fitness along the design path. For example, inspection and test, quality, cost and schedule metrics are important in the model shown in the previous section. The impact of poor metrics can be modeled by increasing the test failure rate and/or the fraction of false negative test results and observing the increase in costs and schedule and number of design starts required.
2. Choose initial conditions (including technologies and products) that will most likely positively influence the design path and produce desired system fitness. For

example in the model in the previous section, choice of technologies, as represented by initial probabilities of selection and initial good design stock levels, has a large impact on path dependence. Seek and choose dominant or exemplar technologies and designs for complex components and systems that have a significant impact on the function and affordability of the end product or service, and concentrate on making design improvements to simple components during the design process [16]. This can be modeled by using different test acceptance probabilities and false negative fractions for the two technologies and observing the number of technology 1 designs versus the number of technology 2 designs accepted.

3. Plan for and get frequent feedback to assess system fitness along the design path. In the previous section, the model provides feedback after every inspection and/or test and when cost or schedule expended reaches critical levels. Quality levels are also indicated after every inspection and/or test.

4. Quantitatively assess alternative paths when declining fitness or obstacles force a path change. Use the “long-jump” feature of the system dynamics model that is described in Section 2, or pursue a long jump during actual design in order to identify and evaluate alternate designs or technologies that are more affordable. Evaluating the alternative cost and benefit, in terms of avoiding negative effects of lock-in (or taking advantage of positive effects), could be accomplished by modeling. This feature is incorporated in the systems dynamic model described above – every design is tested or inspected.

5. Evaluate the effect of random external influences along the design path and attempt to reduce or eliminate adverse impacts if changing the design path reduces system fitness. An example would be loss of a single source supplier of a critical product component. This is modeled in the previous section by a good design probability that generates false negatives that are random events and by extinction events with a very low probability of a technology becoming extinct and its designs being regenerated.

6. Occasionally search the adjacent landscape and attempt to discover paths to higher peaks. This is a variance of the “long-jump” search, where the designer or engineer investigates new, exemplar or dominant technologies for applicability to the

product or service under development. Modeling the alternate technology could indicate if it is feasible to incorporate it in the current development.

Strategy	Model Parameters
Model the complete path for a design phase	Run 1: low test failure rates Run 2: high test failure rates Observe where lock-in can occur
Establish clear, measurable requirements and high fidelity metrics	Increase failure or false positive rates over a series of runs – observe cost, schedule and total design starts
Choose initial conditions to positively influence design path and affordability	Choose high failure rates or false positive rates for one technology, low for the other Observe difference in designs accepted
Get frequent feedback on tests and inspections and quality levels	Enter actual average failure values in model and observe predicted cost, schedule, and quality outcomes
Assess alternate paths when fitness declines or obstacles appear	Use extinction event parameters and actual failure data to create a "long jump" to a new start or different technology
Evaluate effects or random events and external influences	Increase false negative rates or use extinction event parameters to model such effects with predicted or real data
Occasionally search the adjacent landscape for paths to higher peaks	Model a new technology along with the current technology using actual values for all parameters and compare results

Table 4. Strategies and Related System Dynamics Model Parameters

Mathematical tools and techniques, such as nonlinear probability theory, also might be used to predict the behavior of path dependent systems. The nonlinear Polya process [6, 17] can be used to evaluate nonlinear path dependence using urn functions to statistically analyze and predict future outcomes of the path dependent process. The system dynamics model featured above uses the non-linear Polya process. The model can be used to evaluate a current design process anywhere in the design evolution by entering actual values of exogenous variables up to the current point, and continuing the model of the remaining design process using predicted values or probabilities of exogenous variables under various scenarios.

3.6 Conclusions

Systems engineers and designers need to understand the underlying mechanisms that create, dictate and maintain path dependence, as well as the effects on system design and fitness. These mechanisms include impact of initial conditions, effects of continued positive feedback, and the phenomenon of lock-in. They need to recognize the advantages and disadvantages of lock-in: that lock-in can be an advantage if the design is locked-in due to high fidelity positive feedback or a disadvantage when lock-in caused by low fidelity feedback, and unacceptable cost or other conditions result in lower system fitness and system performance. Systems engineers, designers and managers need to employ effective strategies and methods to take advantage of positive effects of path dependence, and offset its potential negative effects.

Future research challenges include refinement of the systems dynamics model to handle each systems engineering design phase separately and sequentially, improved methods for cost and schedule data accrual, ability to feedback quality levels to the inspection and test process to enable automatic adjustment of failure probabilities with accompanying cost increases, and development of more detailed and flexible extinction and long jump model events.

On a broader scale, testing the improved model in various real-life system design situations using real data would further validate the approach. Likewise, applying the improved model to the strategies and techniques suggested above would establish the value of those strategies and techniques and help to better control the positive and negative impacts of path dependence.

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4. Measuring Fitness of Projects, Products and Technologies Using Data Envelopment Analysis

Abstract

This paper explores the analogy between the fitness of technological systems and the fitness of complex adaptive biological systems, and suggests that fitness landscapes are an appropriate structure upon which to evaluate technological system affordability, or fitness, as well as to improve that fitness. It also suggests that the production possibility set in the data envelopment analysis solution space is a form of a fitness landscape that is suitable for evaluating the efficiency and thus the fitness of R&D projects. The paper describes the use of data envelopment analysis (DEA) to evaluate and select Department of Defense (DoD) research and development (R&D) projects as a new application of DEA. It analyzes the application of DEA models to evaluate and select DoD Corrosion Prevention and Control (CPC) project plans by ranking the efficiency of these projects using a minimal set of input and output fitness variables, Projects submitted for evaluation in 2005, 2006 and 2007 were evaluated using established selection criteria as input and output variables. The same projects were evaluated using a revised set of criteria that consisted of fitness function variables to assess the affordability of those projects. The paper also describes the subsequent application of the DEA project plan evaluation and selection methodology to the DoD Corrosion Prevention and Control Program corrosion R&D project selection process since 2007. The paper addresses Altenberg's generalized NK fitness landscapes, explores the possibility that the production possibility set in the data envelopment analysis solution space is a fitness landscape, and discusses the possible use of DEA to evaluate fitness landscapes. An alternate formulation for measuring fitness when limited data is availability is also presented.

Key words: Data envelopment analysis; project evaluation and selection; fitness; fitness landscapes complex adaptive systems; affordability.

4.1 Introduction

The concept of fitness is widely used to describe the overall capability of a system to perform its primary functions. Biological systems depend on achieving and maintaining a level of fitness that enables them to survive – to avoid or defeat threats to their existence and to procreate [1] . Likewise, the ability of technological systems to effectively perform their intended functions is often defined by the quality management community as fitness for use. Since the 1980s, complexity scientists have been studying how complex adaptive systems – notably biological or natural systems – increase their fitness [2]. And engineers are beginning to use the results of those studies to seek innovative ways to increase the fitness of technological systems [3].

Establishing a baseline of existing fitness, and determining the degree to which fitness is increased (or decreased) as systems proceed through their life cycle, requires techniques to measure and quantify fitness. Fitness landscapes provide one method of portraying system fitness on n-dimensional spaces that provide a structure upon which to analyze and pursue increases in system fitness [3-5]. Several types of fitness landscapes have been developed and applied to the process of evaluating and increasing biological system fitness. The first objective of this paper is to explore the concept of using these landscapes to quantify and measure the fitness of technological systems. This is described in Section 2.

Another approach to quantify and measure system fitness might be to use data envelopment analysis (DEA) to evaluate the relative efficiency of competing technological conversion processes [6]. Since Frenken [3] implies that technological fitness can refer to efficiency, it seems reasonable to investigate the possibility that DEA is a valid approach to quantify and measure fitness. The second objective of this paper is to describe DEA principles that lay the foundation for its use in measuring and evaluating technological system fitness. This is presented in Section 3. The third objective of this paper is to investigate the possibility that the production possibility set in the DEA solution space is a fitness landscape. If certain fitness landscapes such as Altenberg's generalized NK landscape [7] conform to the fundamental production axioms [8], these fitness landscapes can represent a production possibility set. If so, DEA might be considered a valid method for evaluating changes in technological fitness on such fitness landscapes. These concepts are presented in Section 4. As an illustration of the concepts presented in this paper, the Section 5 of the paper describes an application of DEA when quantifying and measuring fitness of technological systems. Specifically, it is used to rank the relative fitness of the U. S. Department of Defense corrosion research and development projects submitted annually for selection and funding [9]. Section 4.6 presents an alternate formulation to measure affordability when there are insufficient data available to use DEA [10].

The primary scientific contribution of this paper is the ability to measure affordability in terms of product or system fitness. A corollary contribution is the potential for DEA to be used as a method for measuring fitness of a wide range of processes, products, services or systems associated with organizations, industries and technologies such as those listed in Section 1.1 – a capability that will require additional research, development and validation.

4.1.1 Background

Data envelopment analysis applications continue to expand as the theory and practice become more mature. Seiford [11] compiled a DEA cyber-bibliography of nearly 2800 DEA articles and dissertations. Earlier DEA applications appear to have focused on social and economic issues, with other broad areas of application being added as the familiarity with, need for, and corresponding methods of performing DEA grew. Cooper, Seiford and Tone [12] reveal that DEA has been used to evaluate the performance of numerous organizations and processes, to assist in organizational benchmarking, to develop additional methods of exploiting data, and to offer new insights into processes that had been evaluated using other approaches. The following list of actual technologically oriented applications, generated from Seiford's [11] DEA bibliography, was up to date as of 2005 and reflects many areas where DEA might be used to evaluate technological fitness.

<u>Commercial utilities</u> - power systems, heating plants, water supply services, sanitation services, household energy, hazardous waste treatment;

Transportation and travel - airports, airlines, railroads, corporate travel management, urban transit, public transportation, municipal bus firms, highway accident sites, highway maintenance patrols, container port industries, road networks, ferry transportation;
Communications and computing - computing, large-scale networks, software development, software maintenance, telecommunications, internet organizations;
Product industries - production, manufacturing, supply chain management, technology selection, machinery, engineering design, building and construction, warehousing and distribution, building maintenance;
Military - logistics, civil reserve air fleet, base maintenance, vehicle maintenance;
Energy - oil refineries, surface coal mining, gas distribution, gas industry, electrical cooperatives.

4.2 Fitness of Technological Systems

The importance of measuring the fitness of projects, products, and technologies, in other words the fitness of technological systems, stems from the need to measure system affordability as described in Chapter 2. There, affordability is defined as *that characteristic of a product that enables decision-makers to procure it when they need it, use it to meet their performance requirements at a level of quality that they demand, use it whenever they need it over the expected life span of the product or service, and procure it for a reasonable cost that falls within their budget for all needed products or services.* Chapter 2 goes on to develop the concept of modeling affordability as fitness and thus equates the affordability of a technological system to its fitness. Chapter 2 also points out that the ability to measure affordability is a requirement that has not been met to date. This chapter responds to that need.

Webster describes fitness in terms of "adaptability and sometimes special readiness for use," and defines it as being adapted to and suitable for a purpose and capable of surviving in the environment [13]. In the quality management world, product fitness is termed fitness for use [14]. In natural systems, which are complex adaptive biological systems that have the genetic capability to produce surviving offspring, fitness is defined as the combined inherited characteristics that produce strength and usefulness in the offspring – the stronger and more useful, the greater the fitness [1]. This similarity between technological and natural systems implies that the fitness of technological systems can be analyzed and measured in the same way as the fitness of natural systems [4].

Conceptually, we can describe fit technological systems in the same terms as fit complex adaptive natural systems. If this is so, fitness attributes associated with specific technologies, materials or processes offer the best set of variables to be evaluated as affordability metrics. Furthermore, if we map the attributes of complex adaptive natural systems to fit technological systems, we find striking life-cycle similarities [15]. For example, natural systems must overcome vulnerabilities during creation, achieve growth using available nutrients, sustain life using scarce nutrients, respond cyclically to a biological clock, achieve a robust survival structure, self-regulate, execute timely repairs to continue effective functioning, perform a useful ecological function, and procreate effectively to assure species survival. A fit, adaptive technological system must overcome R&D vulnerabilities, be developed and implemented using available resources, sustain operation using scarce resources, respond to repeated operational cycles, self-regulate, undergo timely repair to continue effective operation, perform a useful ecological function, and be effectively modified for use as a next generation system.

Dynamic changes in system fitness can be depicted on fitness "landscapes". These landscapes are used to analyze, improve and measure resulting technological fitness. Metaphorically, these landscapes have peaks and valleys, and technological fitness variables define the dimensions of the landscape. In his book *At Home in the Universe*, Kauffman [4] describes a rugged fitness landscape as an ideal structure with which to pursue biological fitness as a metaphor for product fitness. He suggests that technological evolution can be depicted as a search on rugged landscapes. As Kauffman points out, systems increase fitness through searching the fitness landscape and hill climbing. Systems change their location on the fitness landscape by changing values of system traits or attributes. The shape of the fitness landscape has a significant effect on the ability of a system to search for and attain greater heights and thus improve its own fitness. Kauffman introduced the NK landscape model to represent the shape and degree of ruggedness of fitness landscapes, where N is the total number of system attributes and K is the number of individual attribute characteristics with which each of the N attributes is epistatically coupled (operationally linked). The term epistatic coupling, or epistasis, refers to coupling between genes, where the fitness of a gene located at a given place on a chromosome is affected by genes located at other places on the chromosome. In this case, it is used to describe the effect that system attributes could have on other system attributes. These fitness landscapes may be correlated, where peaks of similar altitude are grouped together, or random, where peaks of different altitudes are randomly distributed across the landscape. The degree of ruggedness (from correlated to random) depends on the values of N and K.

Kauffman also describes coupled landscapes where a fitness landscape interacts with another fitness landscape. In *The Origins of Order,* Kauffman [5] describes co-evolution as a process of adaptive moves that deform the coupled NK landscapes of the interacting systems. Each system's fitness and fitness landscape depend on the other systems' fitness. As co-evolving systems co-adapt, and the shape of a fitness landscape changes, the degree of fitness improvement or degradation in a particular system will be dictated by the ability of that system to alter existing attributes or generate new attributes that comply with the changing shape. If attribute changes enable the system to improve its position on the new landscape, the system becomes fitter. So fitness landscapes appear to be appropriate schemata to represent and analyze product fitness.

Frenken [3] points out that technology fitness landscapes are useful representations upon which to conduct local search strategies for technological evolution. Such local search strategies outperform global search strategies because bounded rationality [3, 16] constrains the ability of designers and engineers to generate all possible solutions to complex optimization problems, and economics constrain the ability to perform exhaustive global searches. Kaufmann's NK landscape or Altenberg's generalized NK landscape are useful models upon which to conduct adaptive walks or hill climbing toward local peaks on the landscape, in order to increase technological fitness. Thus, an adaptive walk on a fitness landscape, where an attribute value is changed and the resulting product fitness evaluated at each step until maximum fitness is reached, can suggest fit product designs.

Kauffman's NK landscape has a limitation that is overcome by Altenberg's generalized NK landscape. Altenberg's model consists of N elements (key input variables) and F functions (key output variables), where Kaufman's model requires the number of elements to equal the number of functions. In Altenberg's model, the parameter K is eliminated. Instead, each of the elements can influence any positive number of functions and each function can be influenced by any positive number of elements. The number of functions influenced by one specific element is called the pleiotropy of that element, and the number of elements influencing one specific function is called the polygeny of that function.

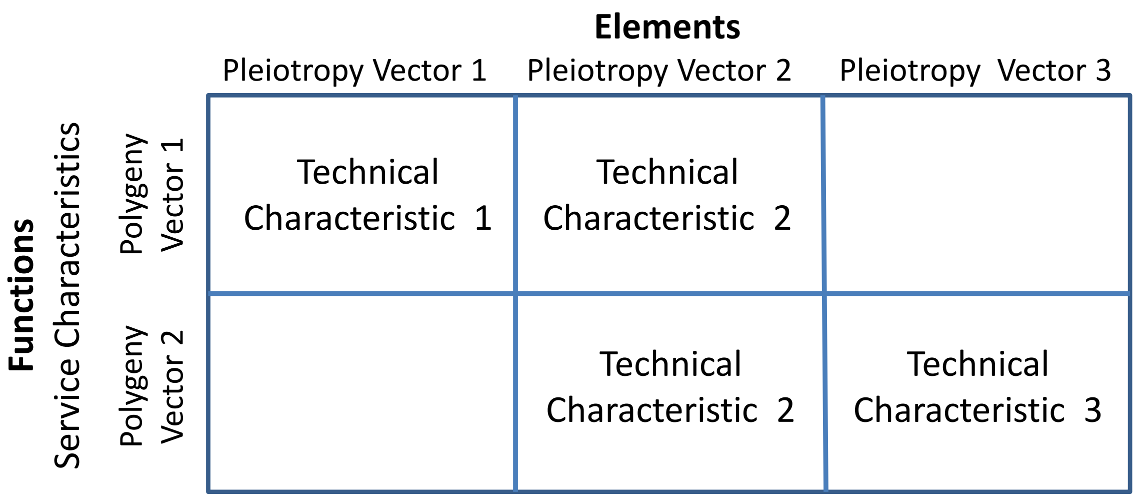

Figure 6. Pleiotropy–Polygeny Map of Elements and Functions

Thus, the structure of epistatic relations between inputs and outputs is shown in the Figure 6 map, where each column reflects the pleiotropy vector associated with three elements (technical characteristics in production terms), and each row reflects a polygeny vector associated with two functions (service characteristics in production terms). The pleiotropy of technical characteristics 1 and 3 is one. The pleiotropy of technical characteristic 2 is two. And the polygeny of both service characteristics is two.

This avoids the use of the K parameter[12], which is important if DEA is to be used to evaluate technological system fitness, since the number of inputs need not equal the number of outputs in DEA. However, all DEA input variables influence all DEA output

[12] Kauffman's NK landscape is a special case of Altenberg's generalized landscape where F equals N and each function's polygeny equals K+1.

variables and all inputs are transformed into outputs through the production function F. Altenberg's generalized landscape also allows vectors of input variables associated with each function to be represented on a fitness landscape and to be used to evaluate the fitness of alternative technological systems or to improve the fitness of a specific system [3]. The dimensions of the landscape are defined by the key variables that contribute to a system's fitness and a vector's position on the landscape at any particular time is determined by the key variable values at that time. If all key variables are independent, increasing the value of one will increase the value of the vector. However, variables are frequently interdependent, and increasing the value of one may decrease the value of another such that the value of the resultant vector may decrease; a concept also found in DEA, where inputs can be substituted along an isoquant as described in the next section.

4.3 Data Envelopment Analysis (DEA)

Data envelopment analysis is a process used to determine the efficiency of any production process. Each observed instance of a production process is termed a decision making unit (DMU) and each DMU is evaluated as part of the aggregated collection of observed instances (DMUs) that depend on similar inputs and result in similar outputs [6],

DEA evaluates the performance of each DMU and quantifies this performance in terms of efficiency. The classic engineering definition of efficiency is the ratio of output to input, expressed as a decimal between 0 and 1, or as a percentage. Since production processes cannot produce more output than input, efficiency cannot exceed 1. DEA is concerned with technical efficiency, which typically involves quantities of inputs and outputs. However, DEA evaluates technical, allocative (cost minimizing), revenue maximizing, and profit maximizing efficiency. Triantis [17] describes the output increasing measure of technical efficiency as a measure of the maximum level of output possible from a bundle of inputs compared to the actual level of output from that bundle of inputs. Thus, if a set of DMUs associated with a specific production process (specific bundle of inputs) produce different levels of outputs, each DMU will have a technical efficiency determined by that DMU's output, and that efficiency will depend on the values of the outputs produced from the input bundle. Those DMUs with the maximum possible output level will be located on an isoquant of efficient DMUs called the production frontier, and those with less than maximum output will be located inside that production frontier – in other words enveloped by the frontier. The collection of all DMU outputs for a particular production process is termed the production possibility set. So data envelopment analysis is the process of determining and analyzing the efficiency of the production possibility set of DMUs on or enveloped by the production frontier.

Figure 5 graphically presents the concept of technical efficiency where efficiency is considered from the input reducing perspective. The graph depicts two inputs and one output for each of three DMUs where the inputs represent the production possibility set. The two input values for each DMU are depicted on the horizontal and vertical axes. Points A, B, and C have equal DMU output values, with B and C as efficient DMUs located on the y_0 isoquant (the production frontier), and A as an inefficient DMU, whose radial measure of technical efficiency is equal to the ratio of 0P divided by 0A, where P is the point on the radial from the origin of the graph to point A at which the radial intersects the production frontier. The distance between the intersection of the X_2^A input value with the isoquant at $A^{'}$ and A, which is a non-radial measure of efficiency, indicates the amount by which the X_1^A input needs to be decreased to make DMU A efficient, without changing the quantity of X_2^A. Likewise, the segment from $A^{''}$ to A indicates the amount by which the X_2^A input must be decreased to make DMU A efficient without changing the quantity of X_1^A. Note that point P lies on the isoquant and defines the radial set of values of X_1^A and X_2^A which could make DMU A as efficient as DMUs B and C. Point P lies between DMUs B and C and those DMUs are thus identified as the peers of DMU A [17].

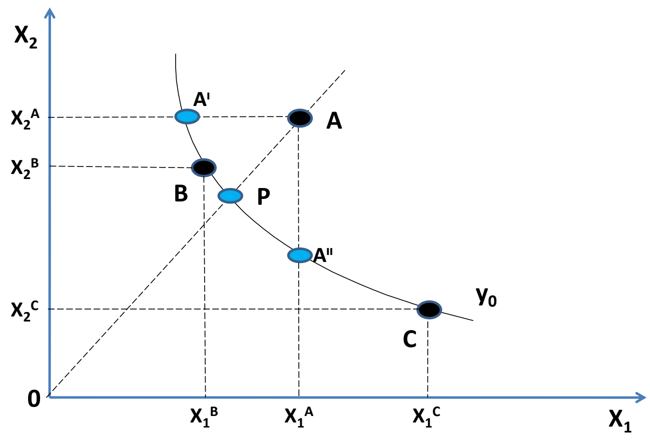

Figure 7. Efficiency with Two Inputs

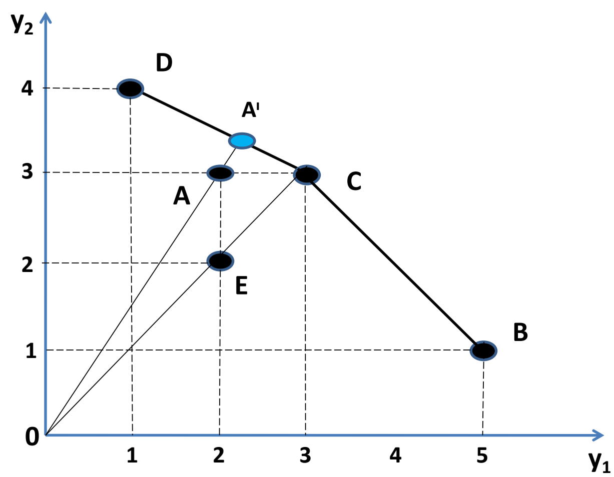

Figure 8. Efficiency with Two Outputs

Figures 5 and 6 showed only one input with two outputs or two inputs with one output. However, DEA can deal with multiple inputs and/or outputs.

Figure 6 represents technical efficiency from the output increasing point of view. The lines connecting the efficient DMUs B, C and D define the production frontier. One input provides two different outputs for each DMU. In this case, DMUs A and E are the inefficient DMUs. The radial efficiency of DMU A is determined by the ratio of the radial distance from the origin to DMU A divided by the radial distance from the origin to the intersection with the production frontier at A'.). Likewise, the radial efficiency of DMU E is determined by the ratio of the radial distance from the origin to DMU E divided by the radial distance from the origin to the intersection with the production frontier at C. The peer set for DMU A is DMUs C and D, while DMU E has a single peer, DMU C, since both lie on the same radial from the origin. The inefficient DMUs can be made efficient by changing the set of outputs to values that lie on the production frontier [17].

DEA uses mathematical and linear programming formulations to evaluate the efficiency of the set of outputs resulting from the conversion of a set of inputs for each DMU. More specifically, for DEA, efficiency is evaluated by dividing the sum of the weighted output variables by the sum of the weighted input variables for each DMU. Since technological systems can be thought of representations of the production process where inputs are transformed into outputs, DEA is an appropriate approach for measuring the efficiency of technological systems.

The underlying mathematical programming takes the two forms of minimizing input or maximizing output formulations that are consistent with the input reducing and output increasing notions of efficiency. The following formulations are the envelopment formulations associated with the computation of efficiency for variable returns to scale technologies. The formulation for minimizing input is [17]:

$$\min_{z} \theta \tag{1}$$

Subject to:

$$\sum_{j=1}^{n} z_j x_{ij} \leq \theta x_i^0 \quad i = 1,2,\dots,m \tag{2}$$

$$\sum_{j=1}^{n} z_j y_{rj} \geq y_r^0 \quad r = 1,2,\dots,t \tag{3}$$

$$\sum_{j=1}^{n} z_j = 1 \tag{4}$$

And the formulation for maximizing output is [17]

$$\max_{z} \theta \tag{5}$$

Subject to:

$$\sum_{j=1}^{n} z_j x_{ij} \leq x_i^0 \quad i = 1,2,\dots,m \tag{6}$$

$$(\sum_{j=1}^{n} z_j y_{rj} \geq \theta y_r^0 \quad r = 1,2,\dots,t \tag{7}$$

$$\sum_{j=1}^{n} z_j = 1 \tag{8}$$

Where

n = number of DMUs

t = number of outputs

m = number of inputs

$y_{rj=}$ output r produced by DMU_j

$x_{ij=}$ input i used by DMU_j

$z_{j=}$ weight given to DMU_j

One of the unique features of DEA is its capacity to simultaneously process variables with different dimensional units and measurement scales [13]. In most applications, variables represented by interval scales are used [9].

DEA has been used by the author to evaluate fitness of systems, but using DEA for improving fitness, has not been explored6. However, DEA identifies peer groups for inefficient DMUs – one or more DMUs that indicate how an inefficient DMU can be improved. Areas for improvement associated with each key variable are identified, and amount of potential improvement is quantified in terms of excess input to the DMU or shortage in output from the DMU [6]. These formulations can be compared to those in Section 4.6 of this paper.

4.4 DEA Production Possibility Set as a Fitness Landscape

The production possibility set or solution space in which DMUs are evaluated by DEA can be thought of as an n-dimensional landscape where the efficiency values are points on the surface of the landscape. Efficient DMUs are located at the peaks of the landscape and a surface passing through those peaks represents the frontier of the landscape. All non-efficient DMUs would be located on ridges or in valleys between the peaks and enveloped by the frontier, with their relative efficiency dictating their location on slopes or in valleys of the landscape. There are strong indications that the DEA solution space is a fitness landscape [3] and that it may even be an NK landscape with instances of epistatic coupling between traits of the key variables evaluated by the DEA model since it is assumed that each input affects each output. If the DEA solution space is a fitness

[13] Measurement scales include ratio, interval, ordinal and nominal scales. Ratio scales compare an attribute to a baseline, as in length. Interval scales quantify the difference between attributes, as in temperature. Ordinal scales define the order in which attributes are ranked from highest to lowest as in preferences. Nominal scales distinguish between attributes as in colors or numbered pages. However, the implication of using different scales in the DEA formulations is an open question in the literature.

landscape, it is an appropriate tool to evaluate the *relative* affordability of alternative technological systems designs [18].

The production possibility set is defined as the region enclosed by the boundary (frontier) of efficient DMUs and the DMUs at the extremities of the boundary [6]. Since the boundary is defined by the locus of output vectors of efficient DMUs, and the vectors of the inefficient DMUs are contained within the production possibility set boundary, the production possibility set is a vector space such as is found in fitness landscapes. In other words, it appears that the DEA solution space is a fitness landscape of output vectors that constitute the production possibility set – in fact that it is an NK landscape where every input affects every output.

As shown in Chapter 2, Altenberg's generalized NK model can be expressed mathematically as a vector for each function F, where F is an output from one or more inputs:

$$F_j = \sum_{i=1}^{n} N_{ij}\, w_{ij}\; j = 1,2, \dots m \tag{9}$$

where

n = number of elements N

m = number of functions F

N_{ij} = input elements affecting function F_j

w_{ij} = weights applied to input elements (if any)

F_j = output vector of N_{ij}

The DEA mathematical formulation for efficiency of a DMU contains two vectors as shown in the following formulation, where the numerator is the output vector and the denominator is an input vector. Each u_s is a weight applied to the output variables and each v_m is a weight applied to the input variables. In the DEA solution space, the bundle of output vectors constitutes the production possibility set.

$$\max_{v,u} \theta = \frac{u_1 y_1 + u_2 y_2 + \dots + u_s y_s}{v_1 x_1 + v_2 x_2 + \dots + v_m x_m} \tag{10}$$

Since the NK landscape formulation shows that the landscape contains output vectors produced by weighted input vectors, and it can be assumed that the DEA production possibility set of output vectors is contained in an NK type fitness landscape, it remains to be shown that an NK fitness landscape will indeed accommodate a production possibility set. Input vectors in the generalized NK landscape can represent the DEA input vectors, and output vectors in the NK landscape can represent DEA output vectors. DEA computes weights for each input and output variable to maximize each DMU's opportunity to be efficient [6]. The generalized NK model also allows weighted input and output variables to indicate the importance of particular elements and functions [3].

Altenberg's generalized NK landscape appears to be a technology landscape that reflects many features of the DEA production possibility set. If so, DEA might be useful in evaluating the fitness of technological systems that can be characterized on the generalized NK landscape. This means that the generalized NK landscape of input and output variables should have the same structure as the production possibility set or DEA solution space, and the generalized NK landscape must conform to the same production axioms that define the DEA production possibility set.

The following production axioms [8] that apply to the DEA solution space can also apply to generalized NK fitness landscapes since these axioms do not violate general properties of those generalized NK fitness landscapes. However, all inputs and outputs on the generalized fitness landscapes must be non-negative for the axioms to apply. These axioms are related to technology sets. The definition of a technology set for a specific production process is:

$$T = \{f(x;y): x \in \mathcal{R}_+^N, y \in \mathcal{R}_+^M: x \text{ can produce } y\}$$

where x is a vector of inputs and y is a vector of outputs such that y can be produced from x. The output set P maps inputs $x \in \mathcal{R}_+^n$ into subsets of outputs, for example $P: \in \mathcal{R}_+^N \Rightarrow 2\mathcal{R}_+^M$. The output correspondence set P(x) for a specific technology is the set of all output vectors $y \in \mathcal{R}_+^M$ that can be obtained from input vector $x \in \mathcal{R}_+^N$. Conversely, the input set P(y) is the set of all input vectors $x \in \mathcal{R}_+^N$ that can produce output vector $y \in \mathcal{R}_+^M$. The axioms are as follows:

1a. $0 \in P(x), \forall x \in \mathfrak{R}_{+}^{N}$

Inactivity axiom: For all values of the input vectors x in the input space $\mathfrak{R}_{+}^{N}$, the output correspondence of the vectors can be zero. Thus, any combination of inputs can produce no outputs if all output vector values are zero.

1b. $y \notin P(x = 0), if\ y > 0$

No free lunch axiom: The output vectors are not a member of the output correspondence set if the input vectors are 0 and the output vectors are greater than zero. In other words, the output is from some input not in the input space.

2a. $If\ y \in P(x) \wedge \lambda \geq 1 \Rightarrow y \in P(\lambda x)$

Weak input disposability axiom: If the output vectors are members of the output correspondence set and the weighting factor (λ) is greater than 1, then the output vectors are members of the output correspondence set of weighted input vectors. In other words, the output will be at least what it would be without the weighting factor. But if the weighting factor is less than 1, the output vectors are not a member of the output correspondence set.

2b. $If\ y \in P(\breve{x}) \wedge x \geq \breve{x} \Rightarrow y \in P(x)$

Strong input disposability axiom: If the output vectors are members of the output correspondence set of original input vectors and the original input vector values are increased, the output vectors are members of the output correspondence set of increased input vectors. That means that the output must be at least what it was before the increase in input (from axiom 1a).

3a. $If\ y \in P(x) \wedge 0 \leq \varphi \leq 1 \Rightarrow \varphi y \in P(x)$

Weak output disposability axiom: If the output vectors are members of the output correspondence set and an output weighting factor is a fraction between 0 and 1, then the fractional output vectors are members of the output correspondence set of input vectors. This means that subsequent outputs from the same inputs can be less than the initial outputs.

3b. $If\ y \in P(x) \wedge \breve{y} \leq y \Rightarrow \breve{y} \in P(x)$

Strong output disposability axiom: If the output vectors are members of the output correspondence set and a subsequent output is less than initial output, then the reduced output vectors are members of the output correspondence set. This means that subsequent outputs from an inefficient process can include waste that can be disposed of without added cost.

4. $\forall x \in \mathfrak{R}_{+}^{N}, P(x)$ is a bounded set

Scarcity axiom: If all input vectors are a set in the input space, then the output correspondence set of input variables is a bounded set. This means that finite amounts of input can produce only finite amounts of output.

5. $\forall x \in \mathfrak{R}_{+}^{N}, P(x)$ is a closed set

Closedness axiom: If all input vectors are a set in the input space, then the output correspondence set is a closed set. This means that if every vector y_j can be produced from inputs x_i, then x can produce y. This allows for the definition and existence of an isoquant.

6. $\forall x \in S(y) \in \mathfrak{R}_{+}^{N}, if\ 0 \leq \lambda \leq 1 \Rightarrow \lambda x + (1-\lambda)\breve{x} \in S(y)$

Convexity axiom: For all input vectors that are members of the input correspondence set and contained in the input space, and x and $\breve{x}$ are each a series of inputs that can produce y, any weighted combination of x and $\breve{x}$ is a member of the input correspondence set. In other words, any weighted combination of two inputs can produce the same output. This means the resultant of the weighted combination is a convex set.

Since it is assumed from the above that production axioms apply to the generalized NK fitness landscape, it implies that this landscape is equivalent to the DEA production possibility set solution space. This indicates that the DEA model can be used to evaluate the relative efficiency and therefore the fitness of technological systems whose input and output vectors populate a generalized NK fitness landscape. But the issue of the existence and effects of epistatic coupling require further research. It may be that collaborative analysis of the same data in both the DEA model and the generalized NK fitness landscape can produce synergetic results, such that each enhances the other's utility and the combined output surpasses what each approach contributes. However, there are limitations in using DEA to evaluate efficiency and fitness since a minimum number of DMUs must be evaluated to provide sufficient discrimination among the DMUs.[14]

The fact is that the DEA model has been used to evaluate relative efficiency of research and development projects, where efficiency is equated to fitness as suggested by Frenken [3], and thus relative efficiency is related to relative fitness. The next section describes a case study illustrating this capability.

4.5 Case Study: R&D Project Evaluation Using DEA

4.5.1 Background

Each fiscal year (FY), the United States Department of Defense (DoD) Corrosion Prevention and Control (CPC) Program solicits research and development (R&D) project plans that propose solutions to specific corrosion problems through new applications of existing technology or development of new technologies. As of December 2011, nearly 500 project plans had been submitted for evaluation, selection and funding with about 150 projects selected and funded for over $160 million since FY 2005. An evaluation team, composed of members of the DoD acquisition, technology and logistics community, performs the annual evaluation based on established criteria for adjudging the merits of each project. Some of these criteria are quantitative, such as return on investment (ROI), but a number of criteria are qualitative variables – basically measured on an ordinal scale subject to the judgment of the evaluators. In addition, the number of projects selected has been constrained by funding limitations.

There were indications that the evaluation process could be improved. Variances in evaluator qualifications and availability and the biases often inherent in highly subjective evaluation processes could have resulted in inconsistent evaluation and selection. When combined with the number of subjective criteria and the considerable variance associated

[14] Cooper et al [6] point out that the number of degrees of freedom is directly proportional to the number of DMUs and inversely proportional to the number of inputs and outputs. They suggest that $n \geq \max\{m\ x\ s,\ 3(m + s)\}$, where n = number of DMUs, m = number of inputs and s = number of outputs.

with the nature and the application of projects, CPC project evaluation complexity was rapidly increasing.

With this environment of subjectivity and complexity in mind, this case study describes an alternate method of project plan evaluation and selection that was designed to retain the basic CPC approach to evaluation, but to use techniques that account for project complexity and variances as well as evaluator competencies and biases. This method used DEA to generate scores that reflect the relative efficiency of each project compared to all evaluated projects.

The use of DEA to evaluate DoD Corrosion Prevention and Control Program corrosion R&D projects originated as a research project for a graduate course in the design of performance management systems at Virginia Tech [10]. That project assumed that the selection of the best R&D projects within a constrained budget environment depends on a process that evaluates the performance projected for each project relative to the other projects being evaluated. The project also assumed that the input and output variables that are associated with affordability fitness functions [19] offer the best set of variables for evaluating the relative efficiency of each R&D project in a population of relatively homogeneous projects.

Prior to developing a method for using DEA to assist in the evaluation of these corrosion R&D projects, the literature was reviewed to determine if DEA had been applied to the assessment of R&D projects. The review revealed that project evaluation had been conducted using DEA and indicated it would be appropriate for R&D project evaluation. Oral, Kettani and Lang [20] addressed R&D project evaluation methods in a multiple stakeholder environment. They pointed out that R&D project variables usually measure outcomes in dimensions that are not easily compared; evaluators are often stakeholders; and some evaluators may value some evaluation criteria differently than others. DEA helps overcome these inconsistencies by independently applying weights to criteria (variable) values, thus mitigating the problem of how to weigh the criteria. There is a requirement that the set of evaluation criteria be reasonable. Linton, Walsh and Morabito [21] described the most convenient measurement situation as one where R&D projects are evaluated with quantitative metrics that use the same unit of measure. They observed that evaluation of R&D projects using the management science approach of quantitative metrics that use the same unit of measure oversimplifies the R&D project characteristics and potential and limits the utility of the evaluation. The DEA approach was considered superior to economic methods because it can measure efficiency among many projects characterized by high degrees of uncertainty, and can measure qualitative characteristics as well as quantitative ones. Green, Doyle and Cook [22] addressed the DEA measurement issue of ranking candidates that appear on the frontier by suggesting the use of a cross evaluation matrix. Eilat, Golany and Shtub [23] discussed the R&D project selection process in the government environment, where "measurement does not normally include profitability but does include multiple criteria with uncertain or subjective data." Because qualitative and subjective measures become even more dominant and performance is measured by several incomparable outputs, they suggested combining DEA with the balanced scorecard (BSC) to select a project portfolio.

Oral et al [20] suggested a set of input and output criteria suitable for applying DEA to R&D project evaluation and selection. While these criteria are derived for iron and steel industry projects, they are general enough to be translated into a set of variables for any R&D projects. Except for resource requirements, the variables they suggested are associated with output criteria. Cook and Green [24] felt the Charnes, Cooper and Rhodes model would be appropriate for project evaluation because they assumed projects reflect constant returns to scale, which is the property featured in that model. They also observed that if scale aspects should be accounted for, the Banker, Charnes and Cooper model should be used. Eilat et al [23] favored the CCR model as part of their DEA-BSC balanced scorecard model. They did not discuss the effects of returns to scale, but observed that the effects may be non-linear. Thus, the literature search confirmed that DEA is appropriate for evaluating and selecting a portfolio of R&D projects. None of the papers reviewed suggested the use of DEA to evaluate alternate sets of variables or to compare the results of already completed evaluation and selection by conventional methods (that use no mathematical, graphical or economic models) to the results that might have been obtained using DEA. These approaches differ from the research described in the following paragraphs in that affordability-based fitness function values were used in this research as key input and output variables, and fitness was equated to efficiency to rank relative fitness (or affordability) of each research and development project submitted for evaluation.

4.5.2 The DEA Approach

Experimentation with the various DEA models led to the choice of a model considered most likely to produce the desired discrimination between submitted projects. The Banker, Charnes, Cooper variable returns to scale model, input reducing version (BCC-I) [6] was assumed to be the appropriate model based on assumed variable returns to scale. Later, the Charnes, Cooper, Rhodes (CCR) model [6] was employed as suggested by the literature, and produced better discrimination between submitted projects.

Data for use in the DEA model was extracted for 212 project plans submitted over the three years from 2005 through 2007. These data were correlated with the existing evaluation process so the variables assessed by the evaluation team tracked with the variables assessed by the model. The one exception was the actual “scoring” by the evaluation team, which was translated into an acceptability index. This index was based on the data from spreadsheets produced and populated by the CPC evaluators during each of the three years’ evaluations. The affordability (fitness) -based evaluation process was also modeled using data from the project plans or evaluation spreadsheets. However, added fitness indices, based on available data, were created to quantify the breadth of applicability and specific benefits associated with each project.

In order to perform the DEA of the evaluation of project plans, each project plan was designated as a Decision-Making Unit (DMU). Two sets of DEA variables were developed: one set to replicate the existing evaluation system using the criteria that had been used by the evaluation team for three years, and the other set to use fitness variables that reflected affordability-based criteria. Both set of criteria used the same input variables, but only one output variable was shared by both set of criteria. The set of input variables for both sets of criteria consisted of:

Total funds required: The total dollars needed for project completion. This includes the labor, material, facilities, equipment and testing to complete the project and transfer the technology to the user community.

Percent OSD funded: The percent of total funds required to be provided by the DoD, since cost sharing between the DoD and military services is expected for each R&D project.

Period of performance: The time that will be required (in months) to complete the proposed R&D project including research, testing and reporting of results.

The output variables used to assess the existing evaluation system consisted of:

Return on investment (a ratio scale variable)**:** The projected ratio of discounted R&D project savings to investment over a specified period, using the Office of Management and Budget (OMB) guidelines and discount rates.

Project acceptance index (an ordinal scale variable): An index of the relative acceptability of an R&D project as determined by evaluator assessment.

The output variables used by the DEA model as fitness-based evaluation criteria consisted of:

Project acceptance index (an ordinal scale variable)**:** A representation of the projected probability of success of the proposed R&D project, as suggested by Oral, et al.

Predicted savings: The discounted dollar savings expected over the useful life of the technology being developed.

Expected service life: The extent of time (in years) that the technology being developed is expected to be useful until it is replaced by another better technology.

Joint applicability index (an ordinal scale variable): The degree to which the R&D project technology could be used in applications beyond those proposed in the submitted project plan.

Benefits index (an ordinal scale variable): An index of non-quantifiable benefits associated with readiness and safety.

4.5.3 The DEA Evaluation Methodology

Three years of project evaluation and selection data were available with which to analyze the efficiency of projects selected. Input data were collected from 212 R&D project plans submitted over the three-year period from fiscal year 2005 through 2007, and from evaluation spreadsheets created and maintained by the author during the evaluations conducted during each fiscal year.

Each year's data were accrued in two homogenous groups – one group associated with facilities and infrastructure projects and the other group associated with weapon system and equipment projects.[15] This provided data for DMU group sizes ranging from 24 DMUs to 41 DMUs. Other groupings were considered, but the group sizes were too small for a reasonable DEA analysis.

DEA efficiency scores were generated using the Baker, Charnes and Cooper (BCC) model in the DEA Solver software that accompanies the Cooper, Seiford and Tone [6] reference book. The input-decreasing model was used for the final set of runs after experimenting with both input decreasing (BCC-I) and output increasing (BCC-O) models. Three years of weapon systems data and three years of facilities and infrastructure data were run, using both current evaluation criteria and affordability-based criteria for a total of twelve data runs, using the BCC-I model. As expected, the DEA efficiency scores for the same DMUs varied substantially between the data runs using the current evaluation criteria and the runs using affordability-based evaluation criteria.

The sensitivity of the DEA efficiency scores to the individual input and output variables was analyzed. Seventy-eight sensitivity runs were generated, where one variable was eliminated in each run. The results indicated that the DEA BCC-I model was sensitive to all variables. Results of the 12 DEA runs are shown in Table 4. Actual DMUs selected refers to the number of research and development projects actually selected and funded in each of the three fiscal years.

The underlying assumption that DMUs on the DEA frontier constitute the set of benchmark DMUs for R&D project plan evaluation and selection is predicated on the number of DMUs in the evaluation set and the number of input and output variables used in the DEA computation. The minimum number of DMUs modeled in the set of runs was

[15] Infrastructure projects refer to projects associated with structures such as buildings, hangars and piers; facilities such as airfields naval stations, bases, and depots; and utilities such as pipelines, tanks and transmission lines. Weapon systems projects refer to projects associated with warfighting platforms such as army land vehicles, naval vessels, aircraft, and missiles; guns, launchers, sensors and other platform warfighting weaponry and equipment; and support equipment such as auxiliary power units, shop equipment and tools used in direct support and maintenance of platforms and weaponry.

24 and the maximum number of DMUs modeled was 41. The DEA Solver model accommodates a maximum of 50 DMUs, so the DEA Solver was not a limitation. Five variables were used in the current evaluation and selection system models, and eight variables were used in the proposed evaluation and selection system models. The lowest number of DMUs modeled equaled or exceeded the Cooper, Seiford and Tone [6] prescribed minimum of three times the number of input plus output variables. Thus the assumption that the DMUs on the frontier are efficient seems to be reasonable.

Homogeneous Groups	Fiscal Year	Existing Evaluation System			Fitness Evaluation System			Actual DMUs Selected	% DMUs Actually Selected	% on Frontier Selected
		Total DMUs	Efficient DMUs	% DMUs Efficient	Total DMUs	Efficient DMUs	% DMUs Efficient			
Weapon Systems and Equipment	2005	41	14	34%	41	26	63%	14	34%	36%-29%
	2006	41	13	32%	41	24	59%	14	34%	43%-79%
	2007	35	13	37%	35	18	51%	10	29%	70%-70%
Facilities and Infrastructure	2005	24	12	50%	24	17	71%	14	58%	50%-79%
	2006	37	10	27%	37	22	59%	15	41%	40%-87%
	2007	34	12	35%	34	22	65%	12	35%	50%-83%

Table 5. Results of Initial DEA Runs Evaluating Efficiency of Project Evaluation System

This assumption is particularly important in evaluating the proposed R&D project plan evaluation and selection approach. In order to adequately evaluate the DEA efficiency scores and relate them, the benchmark DMUs (those on the DEA frontier) needed to be ranked, since available funding typically falls short of the needed funding for acceptable R&D projects. Cross-evaluation matrices were used to compute the average efficiency score of all DMUs when using the weights assigned to a specific DMU. Then, the average efficiency scores were used to rank those DMUs on the frontier.

The first percentage in the in the Table 4 “% on Frontier Selected” column shows the percent of evaluator selected DMUs that would have been selected if DEA modeling replaced the current evaluation and selection process but retained the current criteria. The second in the Table 1 “% on Frontier Selected” column shows the percent of evaluator selected DMUs that would have been selected if DEA modeling used the fitness criteria. Detailed analysis revealed that the resulting ranking was quite different between the two sets of criteria, so under constrained funding conditions, where projects were funded in rank order until funds were exhausted, different DMUs would have been selected under the fitness-based selection approach. Note that when more weapon system project plans were submitted for evaluation, a lower percentage of the DMUs were selected and funded under the current evaluation and selection method. This implies that using DEA evaluation might be more important as the number of project plans submitted increases, particularly since confidence in DEA efficiency scores increases with the number of DMUs evaluated. Notably, the percent of DMUs selected that are on the frontier dropped under the proposed evaluation method, primarily because the number of DMUs on the frontier increased.

4.5.4 Potential for Improving Efficiency of Specific Project Plans

The DoD project evaluation study produced a significant amount of data that could be used to improve the efficiency of inefficient DMUs. Although this option was not pursued in the project evaluation study, the following tables reveal statistics that show that selected inefficient DMUs might have been made more efficient and perhaps approach operating targets if the technology associated with specific DMUs was deemed to be very important.

Homogeneous Groups	Fiscal Year	Existing Evaluation System							Fitness Evaluation System						
		Total DMUs	In-efficient DMUs	Number of DMUs in Reference Set					Total DMUs	In-efficient DMUs	Number of DMUs in Reference Set				
				1	2	3	4	5			1	2	3	4	5
Weapon Systems and Equipment	2005	41	27	0	10	12	3	2	41	15	0	2	4	6	3
	2006	41	28	4	5	17	2	0	41	17	1	3	5	7	1
	2007	35	22	2	9	4	5	2	35	17	0	5	6	3	3
Facilities and Infrastructure	2005	24	12	0	4	4	4	0	24	7	0	2	5	0	0
	2006	37	27	3	6	4	10	4	37	15	1	3	1	6	4
	2007	34	22	1	7	8	6	0	34	12	0	1	6	2	3

Table 6. Number of Inefficient DMUs and Number of Associated Peers in Reference Sets

Tables 5 and 6 combined show that every inefficient DMU had at least one peer. In fact, 94 percent had more than one peer in the reference set. In the existing evaluation system, there were at least nine peers and in the proposed evaluation system there were at least eleven. This is a strong indication of a high number of DMUs on the production frontier.

Homogeneous Groups	Fiscal Year	Existing Evaluation System					Fitness Evaluation System				
		Total DMUs	Total Peers	Peer range for Inefficient DMUs			Total DMUs	Total Peers	Peer range for Inefficient DMUs		
				Low	µ	High			Low	µ	High
Weapon Systems and Equipment	2005	41	12	3	6.3	15	41	18	1	3.2	10
	2006	41	13	1	5.6	15	41	18	1	2.8	7
	2007	35	9	1	6.9	13	35	11	1	5.1	10
Facilities and Infrastructure	2005	24	10	1	3.6	8	24	11	1	1.7	4
	2006	37	9	4	9.8	16	37	12	1	4.6	10
	2007	34	9	1	6.7	19	34	15	1	2.9	12

Table 7. Number of Peers, Range and Average Number of Inefficient DMUs in Reference Sets

Table 6 shows that efficient DMUs were in the reference set for a range of from one to 19 DMUs, with a mean of about 6.5 DMUs for the existing evaluation system and about 3.5 for the fitness evaluation system. Again, this is an indication of the large number of efficient DMUs. With better discrimination between DMUs, the number of peers would be expected to drop significantly and the size of the reference sets for inefficient DMUs expected to decrease. This should make it easier to analyze variables that could improve efficiency and better enable inefficient DMUs to reach operating targets.

4.5.5 Overall Assessment of DEA Results

The DEA efficiency scores located on the frontier correlated quite well with the R&D projects that were actually selected over the three evaluation cycles, considering the probability that the efficiency scores are better indications of true technical efficiency as compared to the subjective evaluation of the current evaluation process. Comparison of DEA efficiency scores under the fitness evaluation method to the R&D projects actually selected indicated substantial improvement in technical efficiency. These initial results led to a decision by DoD Corrosion Prevention and Control Program officials to continue the study and, if feasible, to use DEA in parallel with the existing evaluation method during the fiscal year 2008 project selection process.

4.5.6 Validation and Verification.

After completing the DoD project evaluation DEA analysis, it was concluded that the high percentage of DMUs on the frontier was a symptom of insufficient discrimination between DMUs. This could be due to the number of variables, particularly in the proposed list of variables; possible interdependence between some variables; and the assumption that ordinal scale variables can be included in the DEA analysis.

As described earlier, the initial case study DEA was run using the Banker-Charnes-Cooper (BCC) model based on the assumption of variable returns to scale. The input-decreasing version of the model (BCC–I) was selected since test runs indicated that version generated fewer projects on the frontier. While there was some correlation between the DEA results and the actual projects during the first set of data runs, the data did not strongly support the assumption that the DEA model would accurately replicate the existing evaluation process. One concern was the percent of projects on the frontier – it was higher than anticipated. Some variance was expected since evaluator judgment could have eliminated some good projects from being selected. But a general correspondence between the existing evaluation system results and DEA results using existing criteria was important in order to support the contention that DEA could provide even better results if affordability-based criteria were used for selection.

In the set of data runs that evaluated project efficiency using fitness-based variables, some of the variables were part of the current criteria – in fact, all the input variables remained the same as in the first set of runs. But output variables had been changed to reflect affordability fitness parameters – savings, service life, benefits and joint applicability were added and ROI was removed because it was based on one input and two output variables. Again, results of the DEA model runs were not conclusive. A number of different projects were selected, which was expected, but the percent of projects on the frontier was quite high. The correlation between DEA selected projects and evaluator selected projects varied considerably and no strong conclusion could be reached regarding the value of using fitness-based evaluation factors. This was particularly troubling since there was no assurance that the DEA model selected reasonably replicated the evaluation process.

These results raised questions regarding the choice of DEA model and the choice of variables for the fitness-based evaluation. Generally, given a limited number of DMUs (projects), fewer variables give better results including fewer DMUs on the frontier.

Likewise, the choice of model is sensitive to the characteristic returns to scale of the data being modeled. So the FY 2007 data were rerun using a different mix of fitness-based variables. ROI was added and total investment, savings, and service life were eliminated since they are used to compute ROI. A total of sixteen runs (eight for facilities and eight for weapon systems) were made for the comparison of evaluation parameters and models: the efficiency using the set of six fitness variables (including ROI) was compared to the set of eight fitness variables using the BCC-I, BCC-O (output increasing), CRR-I (Charnes-Cooper-Rhodes) and CRR-O models.

The CRR-I and CRR-O models produced identical results in every case. This indicates that the data might reflect constant returns to scale, a conclusion cited previously in the literature review. The BCC-I model showed better results than the BCC-O model in all cases – there were fewer DMUs on the frontier. Most important, the CRR models produced significantly fewer DMUs on the frontier in all cases. And the six fitness variables (including ROI) produced fewer DMUs on the frontier than the eight fitness variables. The conclusion drawn from these runs was that the CCR-I model processing six fitness variables produces the best results in terms of number of DMUs on the frontier and thus better discrimination between projects. Based on this approach, the FY 2005 and FY 2006 data were run using the BCC-I and CRR-I models to compare the set of six fitness variables to the set of eight fitness variables. Also, FY 2005 facilities data were run using the BCC-O model to validate that BCC-I produced better results as shown in the FY 2007 data runs. The results of the FY 2005 and FY 2006 data runs confirmed the conclusions found in the FY 2007 runs. The CRR-I model using six fitness variables always produced the fewest number of DMUs on the frontier.

Based on these findings, the BCC-I and CRR-I models were used to evaluate DEA results applied to the current selection process. Again, the CRR-I model produced better results in every case for all three fiscal year’s data. More important, the data correlated very well with actual project selection. A high percent of projects actually selected were on the DEA frontier or at the top of the DEA inefficient project rankings. Thus the DEA model quite accurately reflected the evaluation team evaluation and selection process. Likewise, the CRR-I six fitness variable output results were compared to the actual project selection. In every case there are as many or more efficient DMUs on the frontier when fitness based criteria are used instead of the existing criteria. The number of efficient projects exceeded the number selected only twice – FY 2006 weapon systems and FY 2007 facilities. And, in general, the selected projects were among the higher DEA ranked projects, though frequently in different order. These results are as expected – fitness-based parameters should produce different ranking of projects and result in the choice of some different projects based on that ranking. Results of the final verification are shown in Appendix A-2.1.

4.5.7 Real-life Application of DEA to Project Evaluation

In calendar year 2007, during the DoD Corrosion Prevention and Control corrosion R&D project evaluation and selection process for fiscal year 2008, the DEA model was run in parallel with the conventional evaluation process, with evaluators participating in the data generation process for the DEA model. The DEA efficiency rankings were used at times to resolve decisions regarding the selection of some projects. In calendar year 2008, during the evaluation and selection of the fiscal year 2009 projects, DEA efficiency was used as a primary evaluation method in support of the overall evaluation process. Decisions to select projects with lower efficiency rankings were made as exceptions to the DEA ranking order. A ranked list of projects to be selected if added funds became available was developed based on efficiency scores, and used later in the year to select a number of additional projects in the order of ranking. As a safety measure, already selected projects with lower rankings were also ranked, and would have been cancelled in reverse ranking order should funding have been decreased. The actual application of this approach has continued to be successful during project selection of FY2010, FY 2011 and FY 2012 projects. The results of all five years are presented in Appendix A-2.2, where input variables, DEA results, and selection results are tabulated.

Further improvements to the DEA evaluation process have increased its validity and value. For example, the project acceptance index variable has been replaced by a cost of corrosion variable that quantifies the impact the proposed project technology will have on corrosion costs associated with the type of system(s) affected by the proposed project. This is an interval variable based on extensive cost of corrosion studies that replaces an ordinal scale variable, thus enhancing the discrimination of the DEA model in evaluating relative efficiency of all projects.

	Key Variables (Elements)						
Fitness Functions	**ROI**	**Cost of Corrosion**	**Benefits**	**Joint Use**	**% Funded**	**Perform Period**	**Polygeny**
Performance							**3**
Vitality							**2**
Adaptability							**1**
Resource Conversation							**2**
Pleiotropy	**2**	**1**	**2**	**1**	**1**	**1**	

Table 8. Genotype-Phenotype Map of Project Selection Elements and Functions

Table 8 shows the epistatic relations between elements and functions of the DoD research and development project selection evaluation process. Return on investment and benefits have a pleiotropy of 2, vitality and resource conservation have a polygeny of 2, and performance has a polygeny of 3.

4.5.8 Impact on Decision-Making

The objective of the research was to develop an effective R&D project evaluation process that virtually assures that the most efficient projects are selected given annual budget constraints. This objective implicitly affected decision-making.

The decision as to which R&D projects should be selected as candidates for funding and implementation starts with selecting the projects with the best technical approach. This is equivalent to determining the technical efficiency of each project. DEA analysis provides that capability and virtually precludes the bias inherent in subjective types of evaluation. Ranking efficient projects using cross-evaluation scores can enhance subsequent decision regarding which projects should be funded. Thus decisions within budget constraints can be reached more easily.

The process of providing useful feedback to organizations that submit R&D project plans depends on the availability of data that quantify shortfalls. Inefficient R&D projects are not only identified by the DEA models, but their improvement potential in respect to specific input and output variables can be identified. This enables decision-makers to determine whether to resubmit project proposals based on quantified data, but also enables them to improve the future project plan development and publication process. Inefficient project plan data also provide decision makers with data that enable them to assess the evaluation process variables and change evaluation criteria if necessary.

4.6. Alternate Fitness Formulation

Evaluating the affordability of competing technologies when selecting research and development projects for funding has been a problem at the Office of Naval Research (ONR) because there are very little technology data associated with affordability fitness functions with which to assess the affordability of competing technologies [10]. So using the current DEA affordability formulation is not feasible without modification.

The approach to solving this problem is to develop a formulation that will assess fitness of competing technologies without using the DEA model to assess efficiency. An extension to this approach is to develop a formulation that transforms the data used in the technology affordability formulation for use on the DEA model if some affordability fitness function data are available.

For each technology that might be evaluated for development in a research project, specific physical and functional attributes associated with that technology can be selected that make that technology fit for use in the product associated with the research project. ONR has data that can be used for this purpose. Each of these selected attributes can be associated with one or more of the affordability fitness functions.

ONR employs scientists and engineers who are subject matter experts in the technologies used to develop research and development products. These subject matter experts know the degree to which physical and functional attributes of these technologies contribute to the fitness of that technology. The degree to which attributes contribute to each affordability fitness function is designated by an ordinal scale number from 0 to 5, where 0 means no contribution and 5 means total contribution. Table 7 shows an ordinal scale that could be applied to the ranking of technology attribute contribution to an affordability fitness function.

Value	Description
5	Total Contribution to Fitness Function
4	Strong Contribution to Fitness Function
3	Good Contribution to Fitness Function
2	Moderate Contribution to Fitness Function
1	Little Contribution to Fitness Function
0	No Contribution to Fitness Function

Table 9. Scale Values for Assessing Contribution of Attributes to Fitness Functions

Consider that the subject matter experts are provided $\boldsymbol{t}$ technology attribute importance matrices $\boldsymbol{Q_t}$ such that each matrix is for one of $\boldsymbol{t}$ technologies and each matrix contains all subject matter expert rankings in rows $\boldsymbol{i}$ and columns $\boldsymbol{j}$. The number of rows $\boldsymbol{i}$ corresponds to the number of attributes of each technology that the subject matter experts rate. The number of columns $\boldsymbol{j}$ is corresponds to the number of key variables that the subject matter experts address when rating each attribute $\boldsymbol{k_T}$. The subject matter experts complete each matrix $\boldsymbol{Q_t}$ by entering ranking values from Table 1 in the appropriate matrix cell.

Consider also that the subject matter experts and project managers are provided $\boldsymbol{t}$ attribute weight vectors $\boldsymbol{A_t}$, such that each attribute weight vector contains $\boldsymbol{k}$ weights, where $\boldsymbol{k}$ equals the number of attributes associated with technology $\boldsymbol{t}$. The sum of the $\boldsymbol{k}$ weights must equal 1. The subject matter experts and project managers collaborate to assign weights to each $\boldsymbol{A_t}$ that reflect the relative importance of each attribute $\boldsymbol{i}$ to the technology being evaluated.

Furthermore, consider that the subject matter experts and project managers are provided an attribute weight vector $\boldsymbol{W}$, such the attribute weight vector contains $\boldsymbol{j}$ weights, $\boldsymbol{h}$ of which are associated with key output variables and $\boldsymbol{g}$ of which are associated with key input variables. The sum of the $\boldsymbol{h}$ weights must equal 1 and the sum of the $\boldsymbol{g}$ weights must also equal 1. The subject matter experts and project managers collaborate to assign weights to vector $\boldsymbol{W}$ that reflect the relative importance of each key variable $\boldsymbol{j}$ to all technologies being evaluated. In the special case of one key variable for each of the four affordability fitness functions, $\boldsymbol{h} = 3$ and $\boldsymbol{j} = 4$. This means that the first three columns of vector $\boldsymbol{W}$ contain key output variable weights, and the fourth column contains the input variable weight that will equal 1 by definition.

Consider a set of computational vectors $\boldsymbol{M_t}$ for each technology $\boldsymbol{t}$ that contain the computations from which the fitness of each technology is determined. Each column $\boldsymbol{j}$ contains a normalized weighted sum of attribute values for each key variable with which that column is associated. The $\boldsymbol{M_t}$ vector is not necessary, but can be useful for tabulating the weighted contribution of each key variable to the fitness of each technology. The vector can also be used as a row in a table of fitness data for all technologies, and possibly as input to a DEA model.

In order to compute fitness for a technology $\boldsymbol{t}$, begin by determining $\boldsymbol{L_t^I}$, which is the input variable segment of vector $\boldsymbol{M_t}$ and determines the combined sum of the weighted attributes in the $\boldsymbol{j} = \boldsymbol{h} + 1, .., \boldsymbol{g} + \boldsymbol{h}$ key input columns in matrix $\boldsymbol{Q_t}$. The formulation is:

$$L_t^I = \sum_{i=1}^{k} \sum_{j=\hbar+1}^{g+\hbar} A_i W_j Q_{ij} \qquad (11)$$

So, for cells $\boldsymbol{M_{h+1}}$ to $\boldsymbol{M_g}$ in vector $\boldsymbol{M}$, the values are the $\boldsymbol{j}$th result of the above equation, and they reflect the total combined weighted value of the values of each key input variable.

Next, compute $\boldsymbol{L_t^O}$, which is the output variable segment of vector $\boldsymbol{M_t}$ and determines the weighted sum of the weighted attributes in the $\boldsymbol{h}$ key output columns in matrix $\boldsymbol{Q_t}$. The formulation is:

$$L_t^O = \sum_{i=1}^{k} \sum_{j=1}^{\hbar} A_i W_j Q_{ij} / L_t^I \qquad (12)$$

Because combined output cannot exceed combined input, the sum of the weighted output variable values cannot exceed the sum of the weighted input variable values, so the output variable values are normalized by dividing the vector sum by the input vector sum. This formulation guarantees that:

$$\sum_{i=1}^{k} \sum_{j=1}^{\hbar} A_i W_j Q_{ij} \leq L_t^I = \sum_{i=1}^{k} \sum_{j=\hbar+1}^{g+\hbar} A_i W_j Q_{ij}$$

Since fitness has already been defined in terms of efficiency, fitness can be formulated as output over input:

$$f_t = \frac{L_t^O}{{L_t^I}^2} = \frac{\sum_{i=1}^{k}\sum_{j=1}^{\hbar} A_i W_j Q_{ij}}{\left(\sum_{i=1}^{k}\sum_{j=\hbar+1}^{g+\hbar} A_i W_j Q_{ij}\right)^2} \qquad (13)$$

$$subject\ to: \sum_{i=1}^{k} A_i = 1 \qquad (14)$$

$$\sum_{j=1}^{\hbar} W_j = 1, \sum_{j=\hbar+1}^{g+\hbar} W_j = 1 \qquad (15)$$

$$A_i \geq 0, W_i \geq 0, 0 \leq Q_{ij} \leq 1 \qquad (16)$$

The formulation (13) above should allow the introduction of actual variable values in the vector $\boldsymbol{M_t}$ cells. However, added investigation of the formulation is needed to insure that equation remains valid in the case of actual variable data or a mix of weighted ordinal scale data and interval scale data. The above formulations might be simplified if used to generate DEA model inputs, since the DEA model should account for the input-output inequality expressed in the above equation, and the normalizing factor could be eliminated. This possibility is also open to further investigation.

The formulation presented is structured to discriminate between input variables by classifying them according to affordability fitness functions, and using the same ordinal scale to rate the relative importance of an attribute to a technology within that fitness function. If input values are already known based on past experience, this knowledge aids in discriminating between observations. But in the scenarios within which this formulation is expected to be used, the discrimination between observations will be a function of the ability of the subject matter experts' abilities to accurately characterize the attributes of technologies or similar classifications in terms of the key fitness variables, and their association with the affordability fitness functions. If the formulation is sufficiently robust, lack of such discrimination will not have a major effect on results. And perhaps because this may be applied in the high risk-high payoff environment of research and development, discrimination between observations may not be a significant concern.

The formulation itself is designed to characterize fitness in terms of efficiency, by comparing the accumulation of expected outputs to the combination of anticipated inputs, which will produce those outputs. The formulation recognizes the fact that any physical process cannot produce more outputs than the inputs can generate, and contains those outputs' values by allocating the output values of each variable in the ratio of total input variable value to maximum possible input variable value. That formulation is based on the concept that each input will contribute to an output in proportion to the importance of that output to the final product. From the economic viewpoint, it does not allow the process to provide increasing returns.

The formulation simply provides an affordability metric that enables decision makers to determine which alternative or alternatives, from among a population of candidate alternatives, is likely to provide the best overall results in terms of affordability – that is in terms of performance, vitality, adaptability and resource conservation. The formulation is a management decision tool, the output of which can be used in conjunction with other management tools and processes to decide the direction of the technological path and areas in which to invest research and development money. Since there are indications that the formulation can handle actual data either completely, or in conjunction with expert opinion input, the formulation could be used during the production process to evaluate the affordability of the design at intervals throughout the process. In that regard, or in a wider area of application, the formulation could be useful in generating the input data set for use in a DEA model to assess production efficiency.

4.6.1 Example of manual computation of fitness using above formulation

Assume that two technologies, Technology A and Technology B, are being evaluated to determine which alternative is the most affordable to pursue. The attributes to be evaluated have been selected by subject matter experts. They have also determined the relative importance of each fitness function for all technologies being evaluated. Program managers and subject matter experts have determined the relative importance for each key attribute and applied appropriate weights, and the subject matter experts have scored the value of each attribute for each fitness function. The results are shown in the tables 8 and 10, which reflect matrix Q_A and Q_B used as described above to assemble data for the above formulation. The weight row is vector $\boldsymbol{W}$, the weight columns are vectors $\boldsymbol{A_A}$ and

$\boldsymbol{A_B}$, and the total rows are vectors $\boldsymbol{M_A}$ and $\boldsymbol{M_B}$. Output fitness function vectors are performance, vitality, and adaptability, and resources is the input vector.

Technology A		Fitness Functions			
		Performance	Vitality	Adaptability	Resources
Key Attribute	Weight	0.46	0.28	0.26	1
A1	0.21	4	5	2	3
A2	0.18	3	2	2	2
A3	0.3	2	2	4	2
A4	0.17	0	3	3	3
A5	0.14	4	2	3	2

Table 10. Q_A matrix showing data input values and weights for Technology A

Vector $\boldsymbol{M_A}$ is the Total row in Table 9 below for the four fitness function vectors. The normalized $\boldsymbol{M_A}$ vector sum of output vectors, used to compute fitness, is shown in the Total Output Normalized column.

Technology A		Fitness Functions				Total Output Normalized
		Performance	Vitality	Adaptability	Resources	
Key Attribute	Weight	0.46	0.28	0.26	1	
A1	0.21	4	5	2	3	
A2	0.18	3	2	2	2	
A3	0.3	2	2	4	2	
A4	0.17	0	3	3	3	
A5	0.14	4	2	3	2	
Total	1	1.168	0.784	0.757	2.380	1.138

Table 11. Q_A matrix showing weighted fitness function values for Technology A

The fitness as determined by the formulation above is:

$$f_A = \frac{1.168 + .0784 + .757}{2.380^2} = \frac{2.709}{5.664} = \mathbf{.478}$$

The same data tables are provided for technology B.

Technology B		Fitness Functions			
		Performance	Vitality	Adaptability	Resources
Key Attribute	Weight	0.46	0.28	0.26	1
B1	0.32	0	2	2	4
B2	0.21	4	2	5	5
B3	0.25	1	5	0	2
B4	0.22	3	0	3	4

Table 12. Q_B matrix showing data input values and weights for Technology B

Vector $\boldsymbol{M_B}$ is the Total row in Table 11 for the four fitness function vectors. The normalized $\boldsymbol{M_B}$ vector sum of output vectors, used to compute fitness, is shown in the Total Output Normalized column.

Technology B		Fitness Functions				Total Output Normalized
		Performance	Vitality	Adaptability	Resources	
Key Attribute	Weight	0.46	0.28	0.26	1	
B1	0.32	0	2	2	4	
B2	0.21	4	2	5	5	
B3	0.25	1	5	0	2	
B4	0.22	3	0	3	4	
Total	1	0.805	0.647	0.611	3.710	0.556

Table 13. Q_B matrix showing weighted fitness function values for Technology B

The fitness as determined by the formulation above is:

$$f_B = \frac{.805 + .647 + .611}{3.71^2} = \frac{2.063}{13.764} =\mathbf{.15}$$

The comparison shows that Technology A is more affordable than technology B.

4.7 Conclusions

This paper addresses three conjectures associated with affordability landscapes. The first conjecture is that a vector of key affordability fitness variables associated with a DMU represents a point in the production possibility set of all DMUs being evaluated. The second conjecture is that production axioms upon which performance evaluation modeling is based are positively characterized in the affordability production possibility set. The third conjecture is that a performance-based formulation, not based on DEA, can be developed that will optimize the fitness of a specific class of technological systems associated with research and development.

The first conjecture is supported by both major topics discussed in the previous sections. It was shown that affordability fitness vectors associated with key affordability fitness functions define points in an affordability fitness landscape that depict the relative fitness of each production unit represented by each vector. Since the vectors represent finite values of affordability fitness, the isoquant of outermost vector values define the boundary of the solution space of all vectors and thus the space of all possible vector values, which is the production possibility set. The literature supports the concept that landscapes can depict the efficiency of units represented on the landscape and that such efficiency is a measure of fitness. The above examples demonstrate that affordability fitness vectors provide some evidence of the practicality of that concept.

The affordability production possibility set conforms to each of the six production axioms, which supports first two conjectures. This conclusion also supports the use of DEA models in the evaluation of affordability-related DMUs and strengthens the author's contention that the DEA solution space is a fitness landscape, since the literature shows that the DEA model conforms to the production axioms.

Experimentation with actual use of DEA to evaluate the affordability of Department of Defense corrosion research and development projects showed DEA to be a viable method for assessing project fitness. The decision as to which R&D projects should be selected as candidates for funding and implementation starts with selecting the projects with the best technical approach. This is equivalent to determining the technical efficiency of each project. DEA analysis provided that capability and virtually precluded the bias inherent in subjective types of evaluation. Thus decisions regarding which projects to fund under budget constraints were reached more easily.

The process of providing useful feedback to organizations that submit R&D project plans depends on the availability of data that quantifies shortfalls. Inefficient R&D projects are not only identified by the DEA models, but their improvement potential in respect to specific input and output variables can be identified. This enables decision-makers to determine whether to resubmit project proposals based on quantified data, but also enables them to improve the future project plan development and publication process. Inefficient project plan data also provide decision makers with data that enable them to assess the evaluation process variables and change evaluation criteria if necessary.

The third conjecture is supported by the formulation generated for this paper and the application of the formulation to a practical problem with realistic data. This formulation appears to have utility in areas where the affordability of production processes for which a specific set of inputs and outputs have not yet been applied is of interest, and there are little prior data available with which to evaluate the potential production process. This is especially important in the research and development community where expert opinion is the primary source of input data used to make management decisions regarding which technologies to fund in order to advance science and technology.

Clearly there are unanswered questions that require further research. The actual utility of the alternative formulation needs to be verified in practice. Other transformations of output variable data that assure that output does not exceed input need to be developed, to accommodate interval scale data. In a broader sense, more research is needed in the area of fitness landscapes.

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5. Conclusions and Recommendations

5.1 Conclusions

5.1.1 Modeling Affordability as Fitness

Consumers throughout the value chain should be able to benefit from affordable products and services – purchases that perform at the level of quality required by the consumer, perform at that level whenever required during the useful life of that product or service, and do so with minimum consumption of material and financial resources. But despite over ten years of affordability science research at the Office of Naval Research, we still lack a systematic approach to developing affordable systems; and we lack a consistent method for quantifying, measuring and assessing affordability that accommodates a system of non-linear input and output variables with various measurement units.

This dissertation addresses these shortcomings by modeling affordability as fitness of technological systems. It suggests that the characteristics and behaviors of natural systems can be used to provide insight into methods for developing desired characteristics and behaviors of technological systems that will make them affordable. The dissertation describes four fitness functions – performance, vitality, adaptability and resource conservation – functions that provide clues to developers, designers, engineers and manufacturers regarding product or service attributes that will render them more affordable. The dissertation also provides modeling techniques and strategies for system designers and engineers to develop affordable products by analyzing the potential effects of path dependence on fitness attributes. It also demonstrates a potentially effective method for measuring product fitness by using data envelopment analysis to evaluate the relative efficiency of key fitness attributes associated with affordability fitness functions.

The broad impact of this research will be the ability to reap the benefits of more affordable products, both as an end customer, and as a producer who transforms materials received as a customer into products for consumption by customers in the value chain. The by-products should be better performing products with longer, uninterrupted service life that require fewer resources to produce and use.

5.1.2 Path Dependence

Path dependence is not an external artifact of the systems design process, but an inherited characteristic of the design process itself. It provides a convenient structure to assess the fitness of a developing system at any point in its evolution and to choose successive paths that offer the best chance for achieving ultimate system fitness.

The initial starting point and direction of the design path may be dictated by prior conditions, chosen based on prior experience and knowledge, or selected randomly. From that point on, each segment of the design path is normally a function of feedback regarding the fitness of the system along the path. If the feedback is positive, the path will continue in the direction specified by system requirements as interpreted by the systems engineer and designer. If the feedback is negative, a different path direction may be selected. High fidelity feedback provides reliable information with which to make confident design path decisions. Low fidelity feedback provides unreliable information that may lead systems engineers and designers to continue on the wrong path or choose a different path with lower fitness. Continued high fidelity positive feedback usually leads to quicker, more cost-effective results. Continued low fidelity feedback – positive or negative – leads to poor design decisions, excessive cost and possible termination of system development.

While lock-in from path dependence has negative connotations, lock-in can be advantageous if the design is locked in due to high fidelity positive feedback. However, lock-in caused by low fidelity feedback and unacceptable cost or other conditions associated with recovery from design deficiencies will result in lower system fitness and sub-optimal system performance.

Systems engineers and designers must understand the underlying mechanisms that create, dictate and maintain path dependence as well as the effects on system design and fitness. More important, systems engineers and designers need to employ effective strategies and methods to take advantage of positive effects of path dependence and offset its potential negative effects. Through understanding and effectively dealing with path dependence and its effects, systems engineers can conceive of, design, develop and produce products and services with improved system fitness – products and services that are more affordable.

The author modeled the system engineering design process to reinforce these points by graphically illustrating the effects of path dependence and lock-in. The model offers a potential method for analyzing and predicting real-life system design efforts. It could be useful for mapping a future systems design effort or to evaluate and make decisions regarding an effort already underway. Also, the model can be used to augment specific strategies to offset negative effects of path dependence and to take advantage of positive effects.

Traditional systems engineering design alternatives are driven by requirements that are allocated among different system components, and designers keep track of an extensive array of attributes such as cost and performance. In contrast, value-driven design evaluates objective functions over the same set of extensive attributes. The models and approaches presented in this dissertation support the value-driven approach because they assess the effects of path dependence throughout the design evolution on the final product or service.

5.1.3 Measuring Affordability Using DEA

One of the major objectives of the research is to seek methods to quantify and measure affordability. The ONR Affordability Measurement and Prediction Program sought to achieve that objective. But while the AMPP efforts generated many effective methods for developing and producing affordable products, services and systems, the ability to measure affordability largely eluded the participants. AMPP efforts by this author to model affordability as fitness did not yield an effective method to measure affordability, but the complexity sciences and the study of fitness landscapes provided clues regarding where to search.

This research indicates that fitness landscapes – particularly NK fitness landscapes – are viable constructs upon which to search for fitness of technological systems. They have been used by the complexity sciences community to assess and improve the fitness of complex adaptive systems, notably biological ones, and several authors suggest that NK fitness landscapes can be used to assess and improve the fitness of technological systems. But specific methods for doing so needed to be developed.

The introduction to data envelopment analyses provided this author with a potential approach to measuring technological fitness. DEA measures relative efficiency, and since efficiency has been equated to fitness, it offers a method to measure relative fitness. Since the usual reason for measuring affordability is to choose from among a number of alternatives, relative fitness is a very useful parameter. Experimentation with DEA to measure the efficiency, and thus fitness, of corrosion research and development projects submitted to the Department of Defense for selection and funding yielded positive results. This led to further experimentation with DEA and eventual establishment of DEA analysis as the first step in the final DoD corrosion project evaluation process. More important, it established DEA as a viable method for assessing technological fitness or affordability.

Another DoD requirement, the need to select affordable technologies for development by the Office of Naval Research led to the author's development of an alternate formulation to assess affordability, given little hard data. Experimentation with this method is needed to establish its utility in the research and development community and to see if the output of this formulation can form the input and output vectors of the DEA model.

The need for much research and experimentation remains. While analysis indicates that NK fitness landscapes can accommodate the production possibility set, and that the DEA solution space is a generalized NK fitness landscape, associated implications regarding the impact of production functions, path dependence, and feedback need to be investigated and articulated. Nevertheless, the research and experimentation documented in this dissertation reflect a giant step in pursuit of more affordable technological systems and the ability to measure their fitness.

5.2 Recommendations

5.2.1 Modeling Affordability as Fitness

Industrial and systems engineers are often dedicated to maximizing the economic return on sales of goods and services produced by their employers. This raises several questions regarding the role of industrial and systems engineers in the broader community of both producers and consumers. Should industrial and systems engineers not only be concerned with benefits that accrue to producers, but also be concerned with benefits that accrue to customers in typical sales transactions? More specifically, should industrial and systems engineers have a role in maximizing benefits that accrue to the customers? And, since economic return to employers can be and is measured by industrial and systems engineers, can they also measure those benefits that accrue to the customers?

This author feels that industrial and systems engineers need to understand affordability as it is characterized in this dissertation and be champions for consumers as well as for the producers who employ these engineers. The industrial and systems engineering curriculum at Virginia Tech and other engineering universities should include studies in the complexity sciences since complexity sciences can be related to all industrial and systems engineering disciplines and functions.

A basic complexity sciences course for industrial and systems engineers could feature authors such as Kauffman, Frenken, Holland, Sterman, Waltrop and Arthur, who offer a rich background in complexity sciences, as do a host of others including Nobel Laureates Kenneth Arrow and Murray Gell-Mann. Frenken, for example, suggests practical approaches to applying and analyzing fitness landscapes and using bounded rationality to focus on exemplar systems as an initial condition of systems design.

Engineering core courses should have affordability and fitness concepts woven into their course syllabus. Path dependence principles, impacts and strategies should appear in the Systems Engineering Process (ENGR 5004) course. Affordability concepts and tools can be integrated into the Macroergonomics (ISE 5694) course. The Research in the Design of Performance Measurement Systems (ISE 5144) course provided the basis for the experimentation in affordability fitness measurement, so affordability concepts and practical application would naturally fit in that syllabus. The Management of Quality and

Reliability (ISE 5124) course syllabus is also a natural place to feature affordability and fitness, particularly since quality is frequently defined as fitness for use. As a matter of fact, complexity sciences and affordability content was integrated into one presentation of that course in the 2010 fall semester. Two systems dynamics courses, Applied Systems Engineering (ENGR 5104) and Advanced Dynamic Modeling (ISE 6104), could also feature affordability, particularly emphasizing path dependence.

On a broader scale, the concepts of affordability as fitness and of measuring technological fitness using DEA should be publicized through periodicals, articles and conference presentations. Chapter two should be submitted as an essay to appropriate publications.

5.2.2 Path Dependence

The path dependence model presented in this dissertation is a simple model with minimal feedback and alternative paths. The model should be expanded to enable more detailed characterization and analysis of path dependence in the design of affordable systems. For example, use total design quality level feedback to adjust the inspection and test regimen; model extinction events so only one technology experiences extinction; and model the long jump to respond to quality feedback from either technology.

It will also be useful to experiment with other simulation models, such as discrete event simulation, to evaluate how they can process the relationships, events and types of variables typical of path dependence networks.

The strategies and techniques to use or mitigate the effects of path dependence suggested in the dissertation need to be thoroughly tested, particularly in regards to the use of the system dynamics path dependence model. If the model is expanded as suggested above, the impact of any changes need to be assessed, and the approach to engaging the model in support of strategies or techniques to use or mitigate the effects of path dependence need to be adjusted if necessary.

Chapter three should be submitted to appropriate journals for publication.

5.2.3 Measuring Affordability Using DEA

The relationship between fitness landscapes, particularly the generalized NK fitness landscape; production axioms; the DEA production possibility set solution space; path dependence; and impact of feedback in landscapes and the production possibility set; all need to be addressed and analyzed. While there are strong indications that the DEA solution space is an NK fitness landscape, further investigation of this assumed correspondence is needed. Likewise, further investigation is warranted into the conclusion that the NK landscape conforms to production axioms and accommodates the production function, as defined by the production possibility set.

While path dependence is, by definition, a characteristic of the NK fitness landscape as analysts traverse the landscape using random walks in search of higher system fitness, the use of DEA fitness measurement in the context of successive feedback and improvement on a path through the production possibility set is a concept requiring significant thought, experimentation, modeling and analysis. It is likely that such a pursuit would be a major undertaking, but positive results could be a major breakthrough in using DEA for measuring affordability as fitness as well as measuring fitness in the broader sense of complex adaptive systems fitness.

At a more practical level, DEA assessment should be applied to other instances of project evaluation to substantiate the methods and conclusions featured in this dissertation. In this regard, alternate methods for assessing fitness using concepts such as those described in the last section of Chapter 4 should be pursued or validated to replace or support the use of DEA when a small number of DMUs constrain the use of DEA.

Chapter four should be submitted to appropriate journals for publication.

Appendix A – Path Dependence

A-1 Path Dependence in Design Model Description

The systems design model of path dependence is designed to illustrate the nature of path dependence during the design phases of the systems engineering acquisition cycle, and to show the effects of path dependence during that phase. The units developed are technology design units, which refer to technology development component, subassembly and assembly designs.

The model accommodates two technologies, and, during each period, generates and assigns a technology unit design to one of the two technologies. The total number of technology units to be designed and developed in each sub-phase during the model run is an exogenous variable. The process of assigning a technology unit design to a technology is to allocate the design based on the probability of selecting that technology.

The non-linear Polya process is used to generate the probabilities of selection during each successive period. This model is adapted from Sterman's non-linear Polya process formulation, which generates path dependent results. The degree of path dependence is regulated by an exogenous "sensitivity to proportion" variable. The probability of selecting a specific technology unit is based on the ratio of the previous selection of that type technology unit to the total instances of technology unit selection. Generating a random uniform variable and comparing it to the probability of selection make the actual selection. The probability of selection during each period is modified by random perturbations generated by an exponential function associated with the probability variable. The initial probability of selecting a technology unit is dictated by the exogenous "initial technology" variables, which define the initial values of the two technology unit stocks. Nominally, they each have one technology unit assigned to each stock, which dictates that the initial probability is 0.5 for each technology. However, if it is determined that one technology is dominant; more than one unit can be entered in the initial technology variable.

Every generated design is inspected or tested, where the probability of failure is an exogenous variable. A random uniform variable is generated and compared to the probability of failure to determine if the design is acceptable and can be added to the stock of good designs. However, before being added to the stock of good designs, the probability of the design acceptance being a false negative, also an exogenous variable, is compared to another random uniform variable, and if a false negative, the design is added to the false negative design stock rather than the stock of good designs. Designs in the false negative design stock are later “discovered” to be false negatives, added to the rework stock, and placed in the good design stock after rework is performed.

The model also allows for one or more “extinction” events to be randomly generated. An extinction event is an event that stops the normal design development process and causes the process to start again from the beginning. An extinction event can be used to simulate a random occurrence such as non-availability of critical materials or loss of a sole source supplier. It can also simulate the result of a long jump to a better technology. An exogenous extinction switch controls the extinction event, exogenous lower and upper limits to the time period during which the event(s) will occur, and an exogenous maximum number of extinctions that can occur during a model run.

The model accumulates costs and schedule days required to complete the design. Separate cost data are captured for unit design, for inspection and/or test, for redesign of failed units, and for rework of false negatives. The cost accrued is generated by multiplying exogenous maximum cost variables for design, test, rework or redesign by table values, which determine the percentage of maximum cost that applies to that period of the model run. The resulting costs are accrued in cumulative cost stocks. Total schedule days expended are computed by multiplying total designs accepted by an exogenous average time per design variable.

The model run is completed when the total number of good designs for both technologies equals the “total designs” variable, which defines the number of accepted designs required. The model run can also end if the exogenous lock-in switch is on and either the number of schedule days or the cost exceeds the maximum allowed for either. Initiating another model run with the same values of exogenous variables is performed by changing the exogenous “random number seed” variable. That variable will also change the value of the other random number seeds.

The model variables of interest are the good technology design stocks, the cumulative costs and the total schedule days expended. Other interesting variables are the failure rates and the number of false negatives. By changing the exogenous random number seed variable, the path dependent nature of the process becomes apparent. Initial conditions and early selections dictate which technology will dominate during a specific model run, how much the detailed design will cost, how long it will take, and how extinction events will affect path dependence.

A-2 System Dynamics Model Causal Loop Diagrams

Figure 9. Design, Development and Inspection or Test Activities

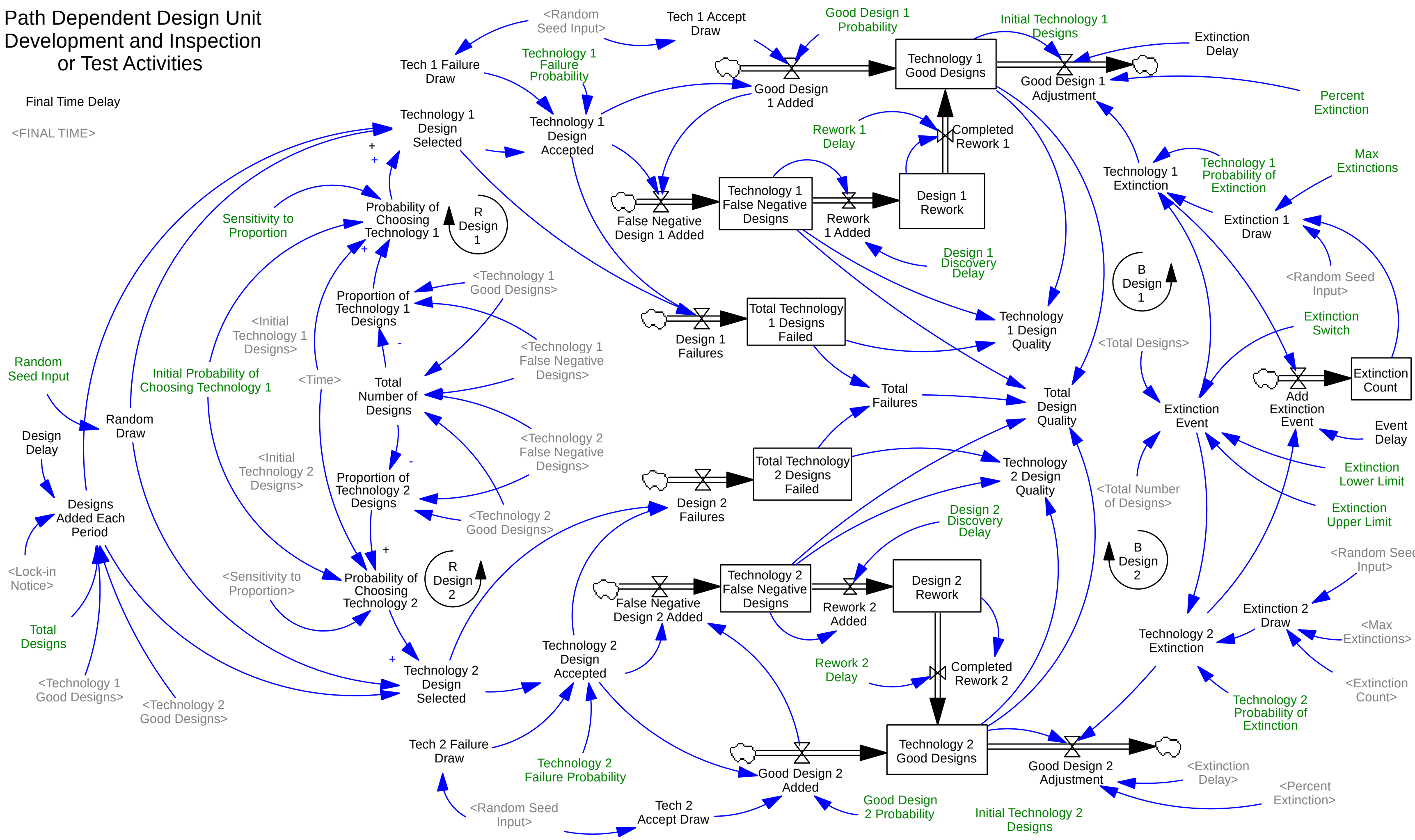
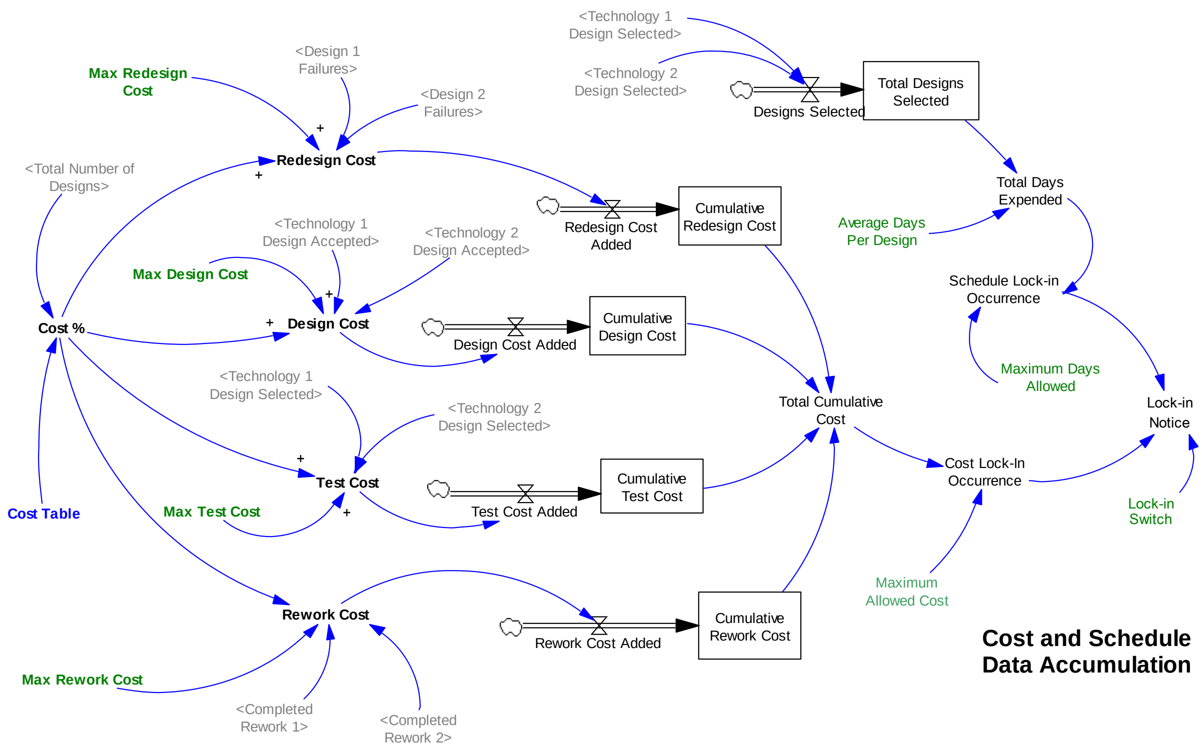


Figure 10. Cost and Schedule Activities



A-3 System Dynamics Model Runs

Table 14. Exogenous Variables Used in Model Runs

The graphs on the following pages were produced using the following parameters. Runs were performed on Vensim DSSDP Software.

		Initial	Feedback					Random Event					Coevolution		
			Low	Med.	High	Lockin	Bias	Low	Med.	High	Lockin	Bias	Low	Med.	High
Changed Exogenous Variables	Dataset	IC	FL	FM	FH	FK	FB	RL	RM	RH	RK	RB	CL	CM	CH
Technology 1 Failure Probability		0.05	0.1	0.3	0.5	0.5	0.5	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.3
Technology 2 Failure Probability		0.05	0.1	0.3	0.5	0.5	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.3
Good Design 1 Probability		1	1	1	1	1	1	0.9	0.7	0.5	0.5	0.5	0.9	0.8	0.7
Good Design 2 Probability		1	1	1	1	1	1	0.9	0.7	0.5	0.5	0.9	0.9	0.8	0.7
Extinction Switch		0	0	0	0	0	0	0	0	0	0	0	1	1	1
Probability of Extinction		0	0	0	0	0	0	0	0	0	0	0	0.01	0.01	0.01
Extinction Lower Limit		**0**	0	0	0	0	0	0	0	0	0	0	0.01	0.01	0.55
Extinction Upper Limit		0	0	0	0	0	0	0	0	0	0	0	0.2	0.5	0.7
Max Extinctions		0	0	0	0	0	0	0	0	0	0	0	1	2	1
Lock-in Switch		0	0	0	0	1	0	0	0	0	1	0	0	0	0
Random number seed 1	1,485														
2	1,732														
3	1,614														
Fixed Exogenous Variables															
Sensitivity to Proportion	7.00														
Initial Probability of Choosing Technology 1	0.50														
Total Designs	500														
Initial Technology 1	1														
Initial Technology 2	1														
Design 1 Discovery Delay	10														
Design 2 Discovery Delay	10														
Rework 1 Delay	4														
Rework 2 Delay	4														
Max Design Cost	20,000														
Max Test Cost	10,000														
Max Redesign Cost	25,000														
Max Rework Cost	25,000														
Average Days Per Design	1.6														
Maximum Days Allowed	1,000														
Maximum Allowed Cost	2,500,000														

A-4 Results of Model Runs Using Above Parameters

Figure 11. Effect of Feedback from Low Test Failure Rate on Path Dependence

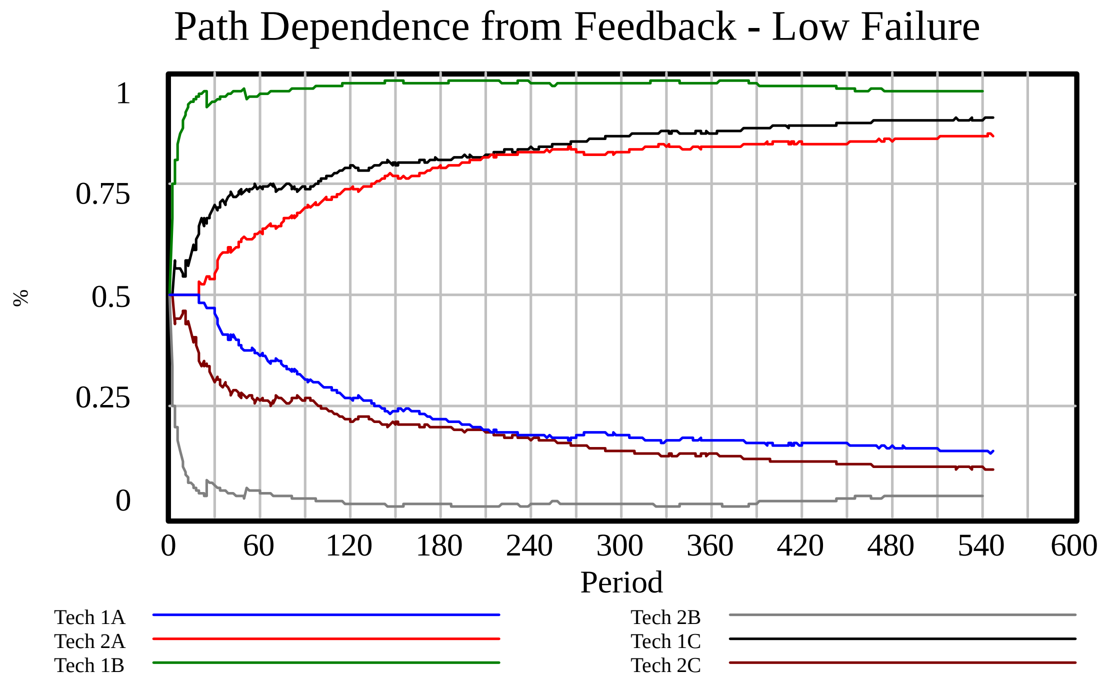


Figure 12. Effect of Feedback from Medium Test Failure Rate on Path Dependence

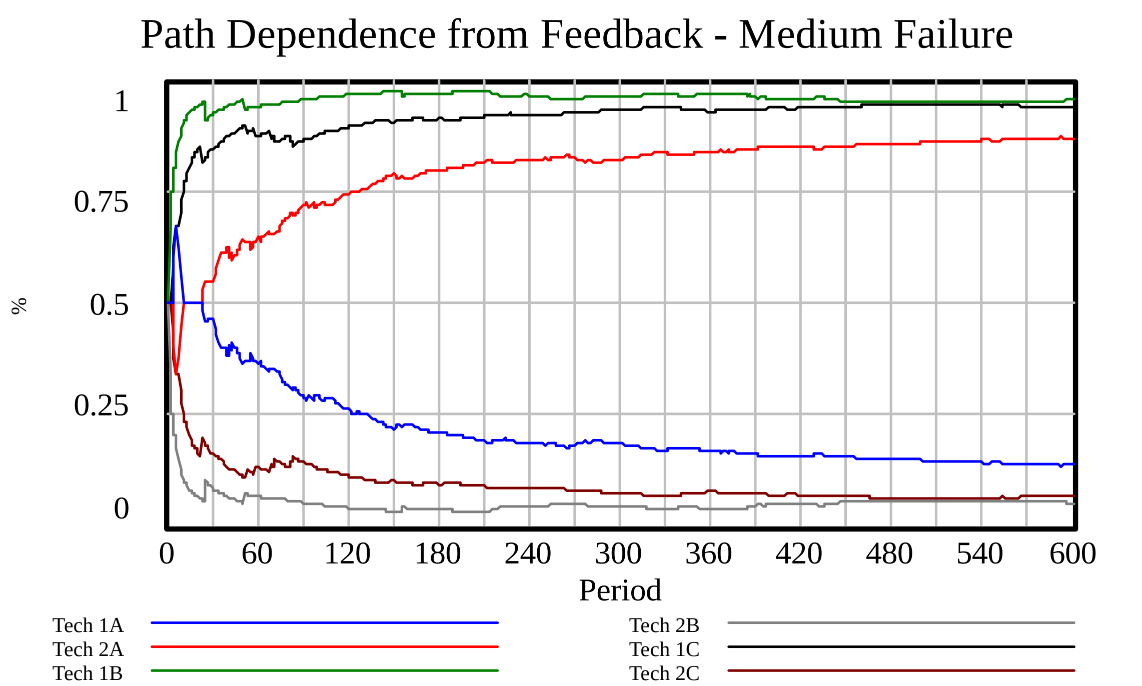


Figure 13. Effect of Feedback from High Test Failure Rate on Path Dependence

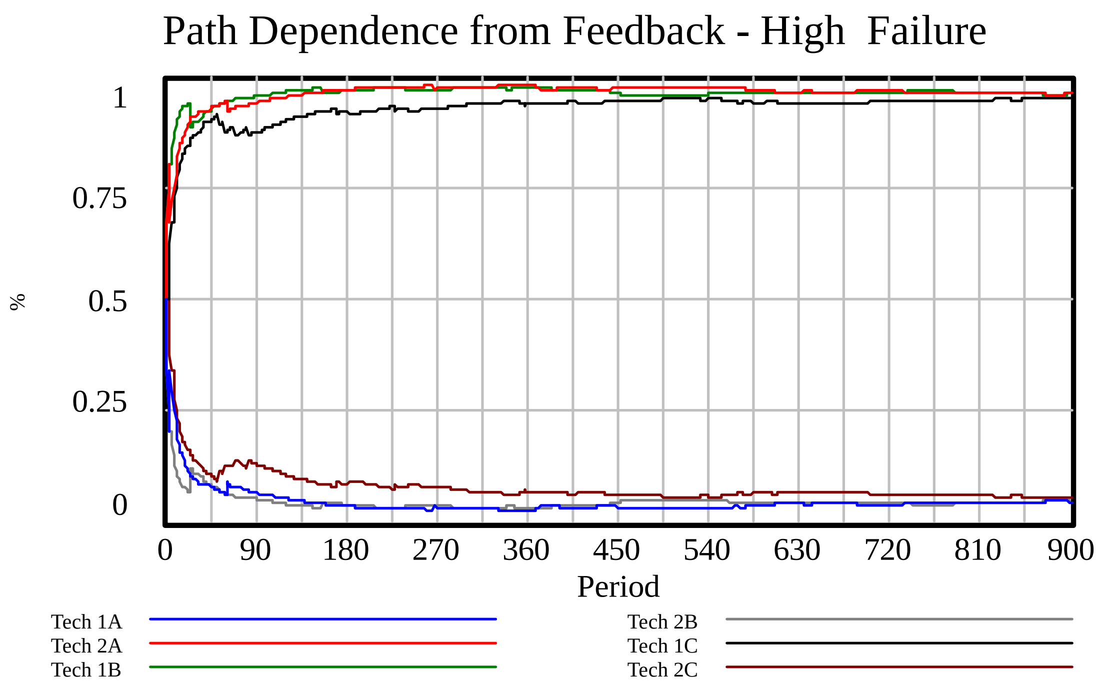


Figure 14. Effect of Feedback from High Failure Rate of One Technology on Path Dependence

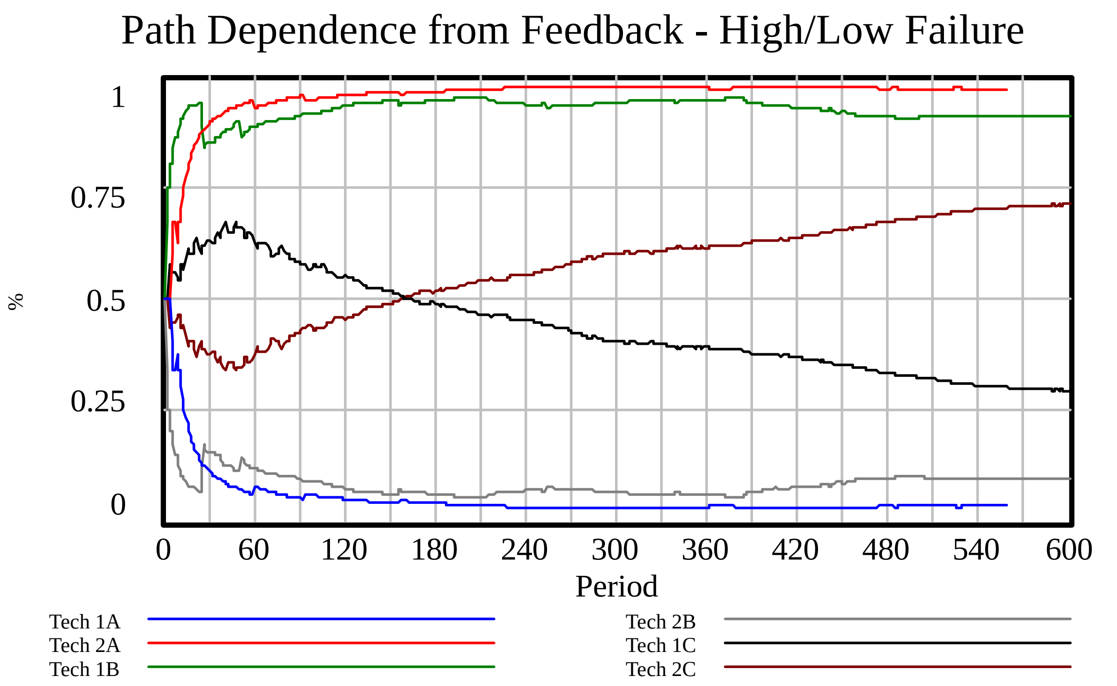
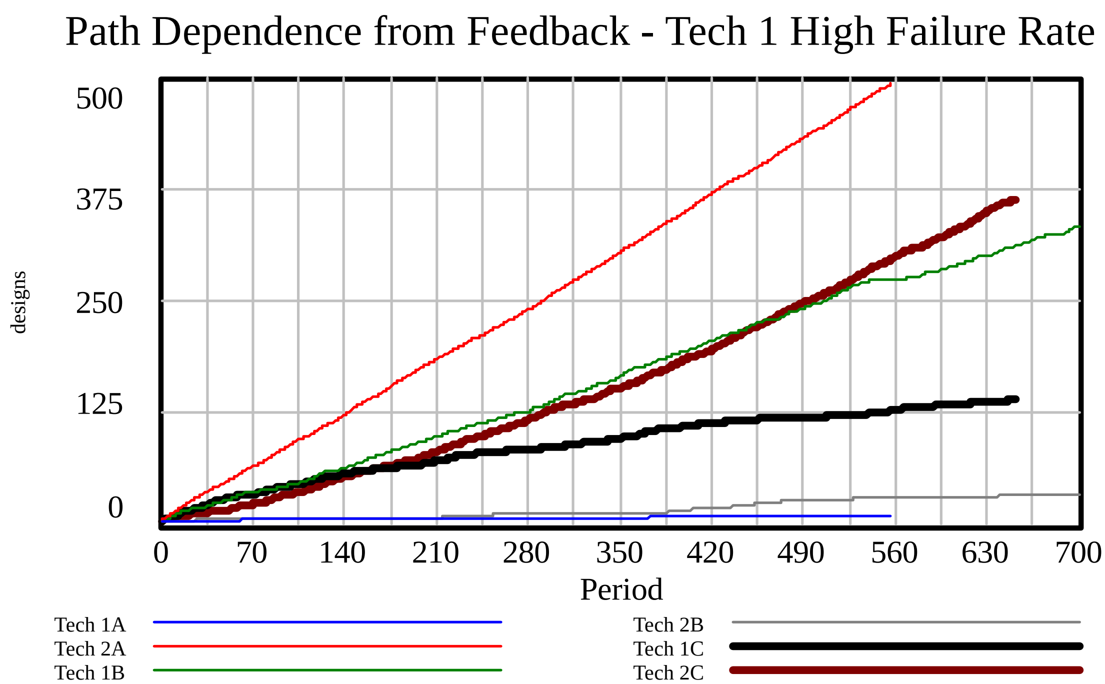


Figure 15. Cause of Crossover in Figure 12



Heavy lines show total good designs accepted during Run C. Technology 1 dominated initially, but high failure rate caused increased acceptance of technology 2 designs, and positive technology 2 feedback reinforced the upward trend of the technology 2 path. In Runs A and B, technology 2 quickly dominated from initiation with less failures.

Figure 16. Effect of Feedback from Low Random Event Rate on Path Dependence

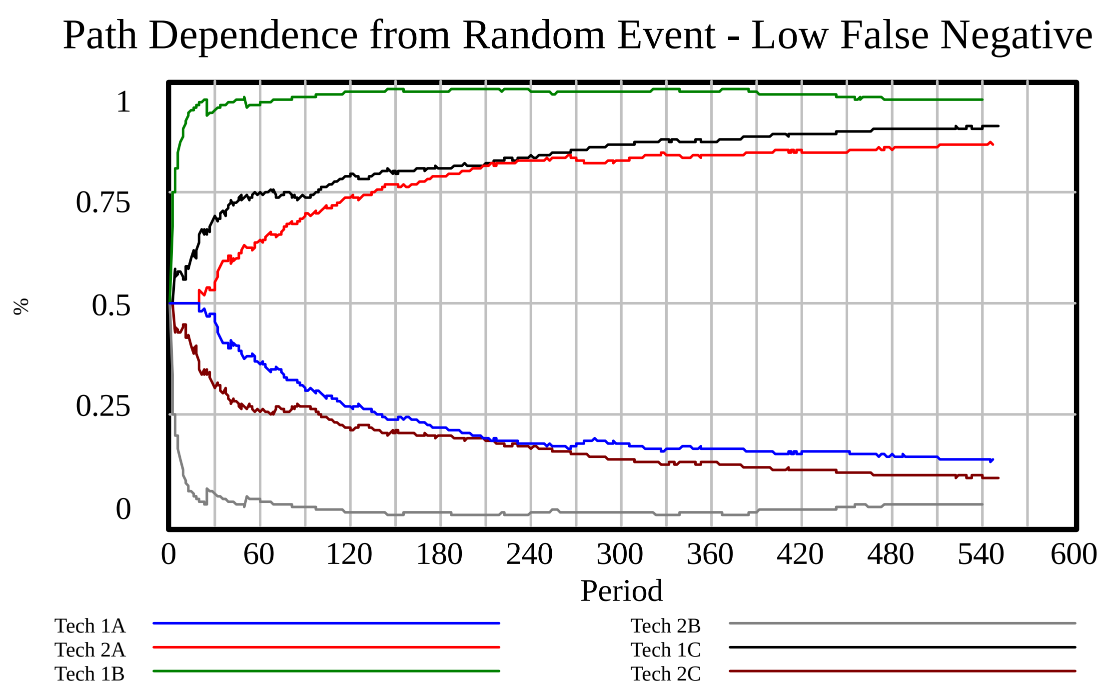


Figure 17. Effect of Feedback from Medium Random Event Rate on Path Dependence

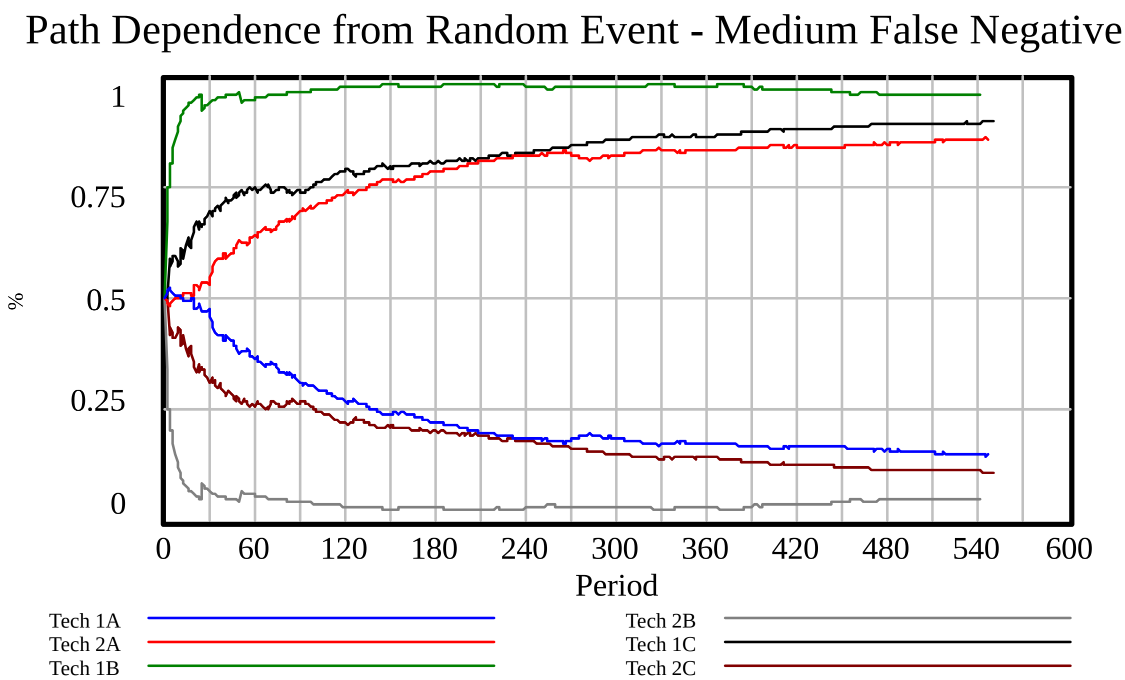


Figure 18. Effect of Feedback from High Random Event Rate on Path Dependence

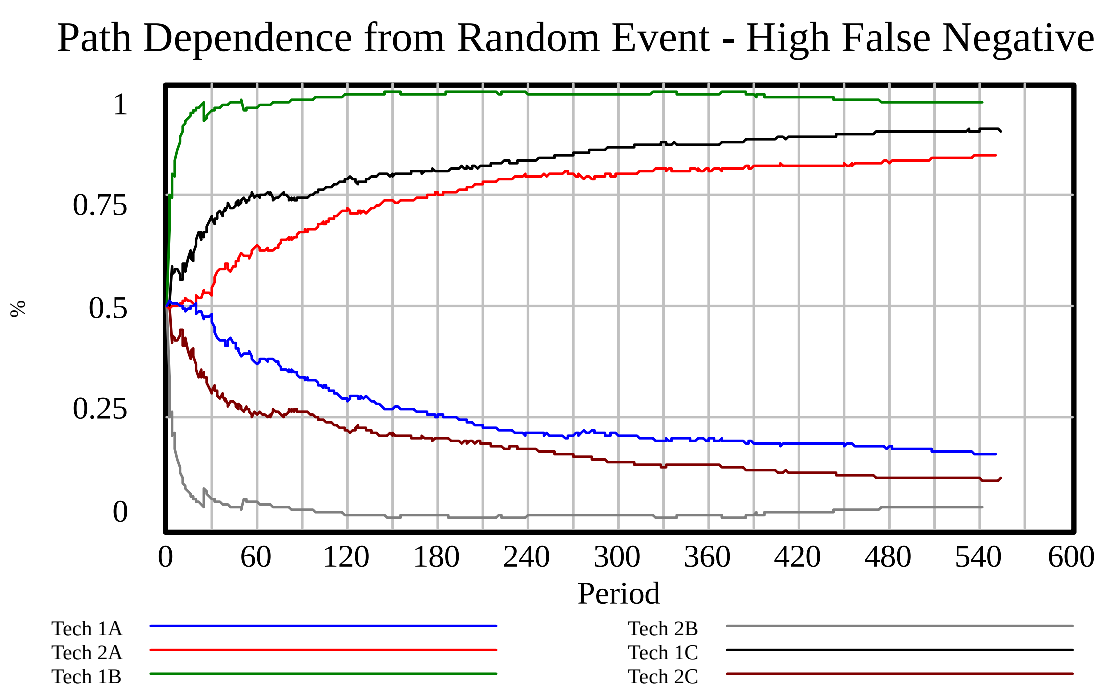


Figure 19. Effect of Feedback from High Random Event Rate of One Technology on Path Dependence

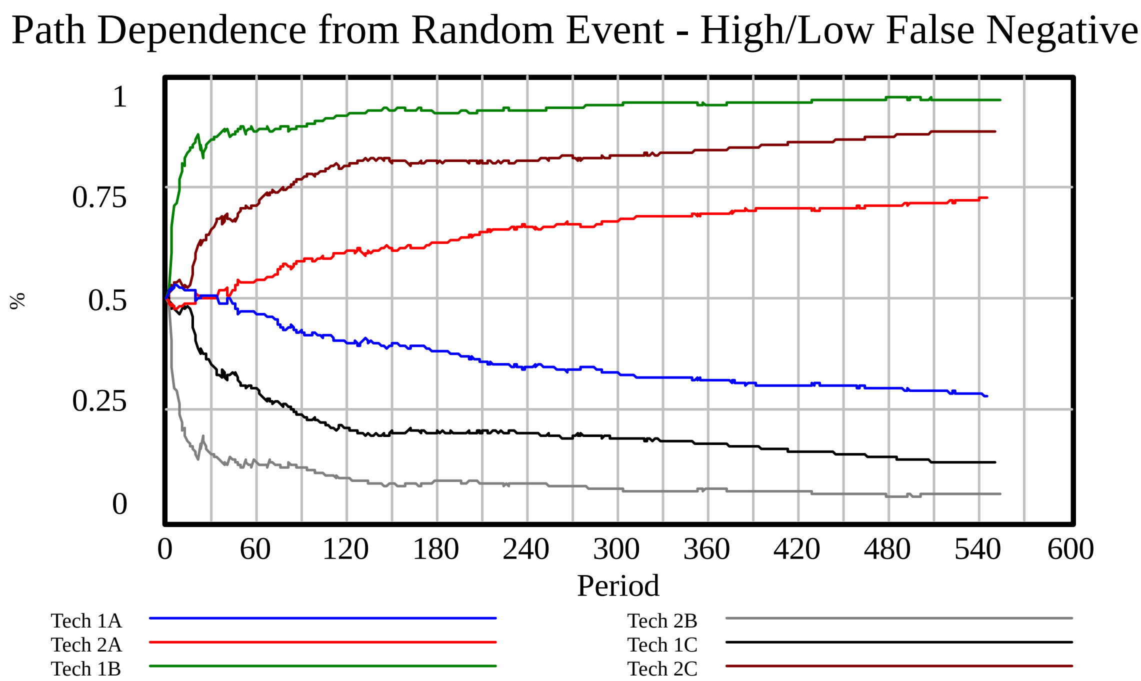


Figure 20. Effect of Coevolution with Combination of Low Failure & Low False Negative Rates on Path Dependence

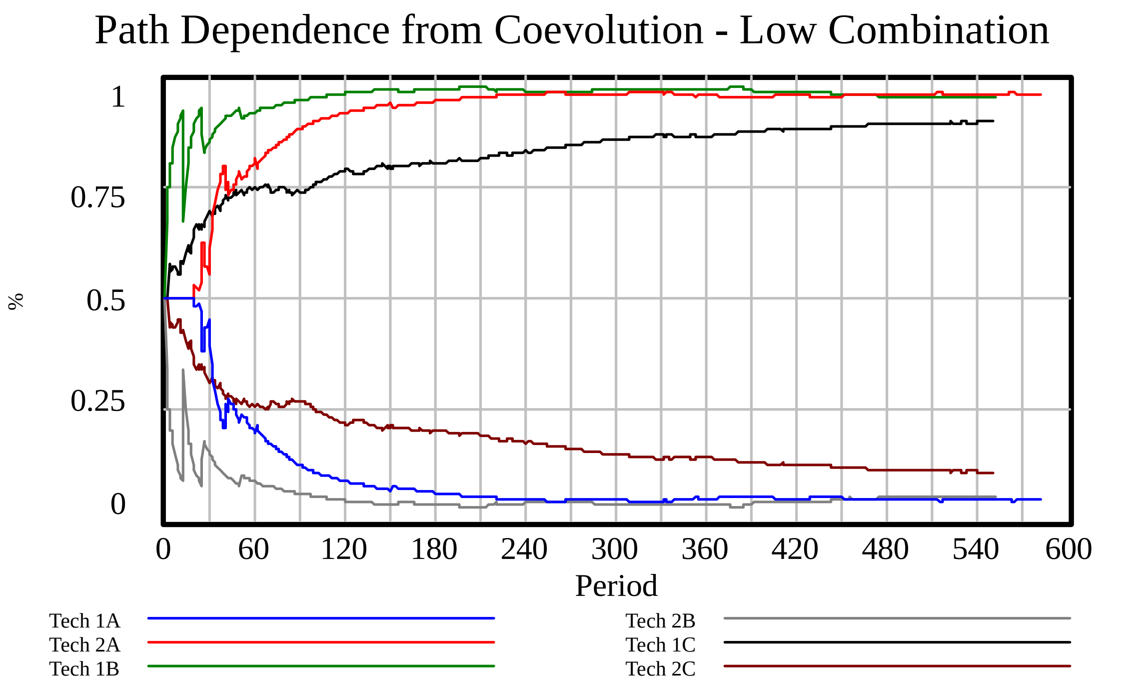


Figure 21. Effect of Coevolution with Combination of Medium Failure & Low False Negative Rates on Path Dependence

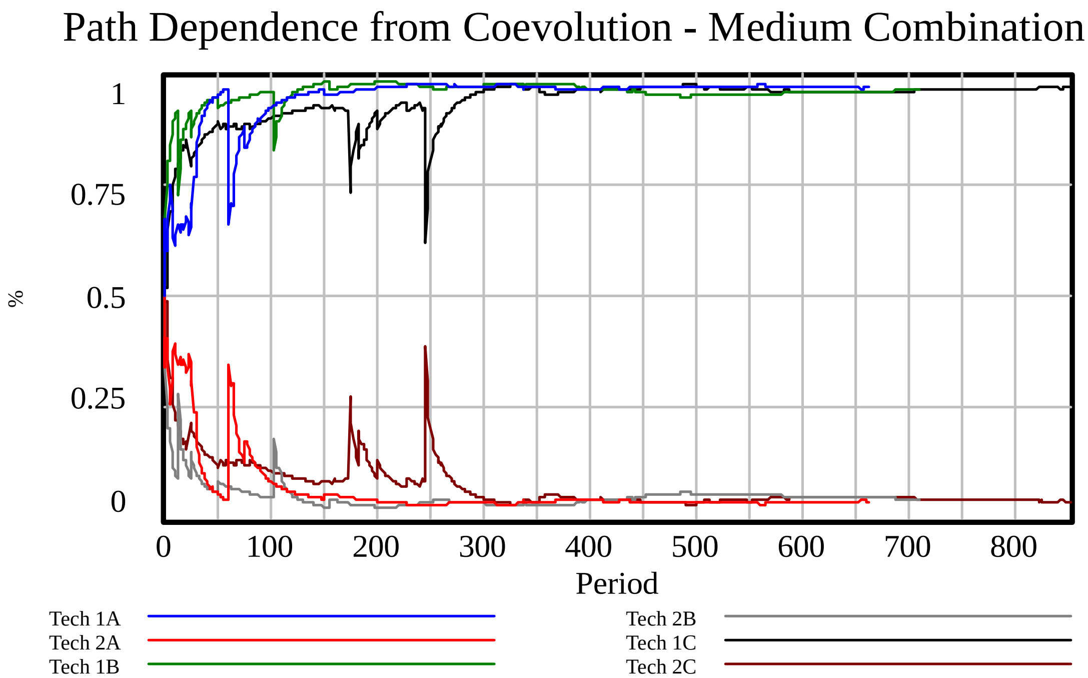


Figure 22. Points Where Extinction Events on Low and Medium Combinations Occurred Causing Design Restart

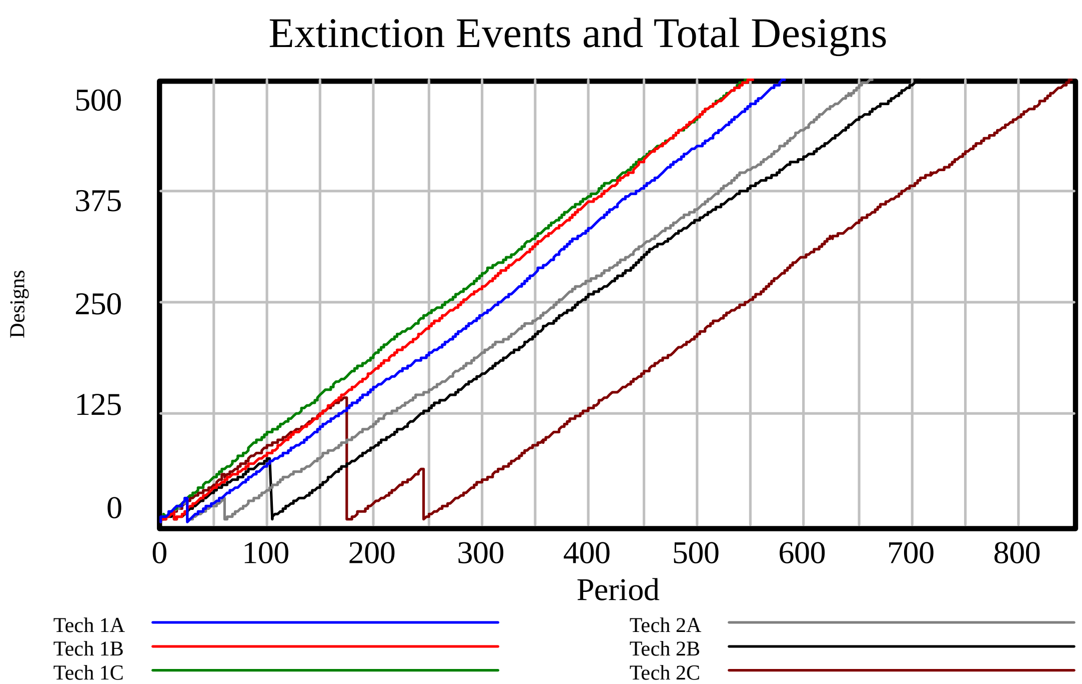


Figure 23. Effect of Coevolution (Long Jump) with Combination of High Failure & Low False Negative Rates on Path Dependence

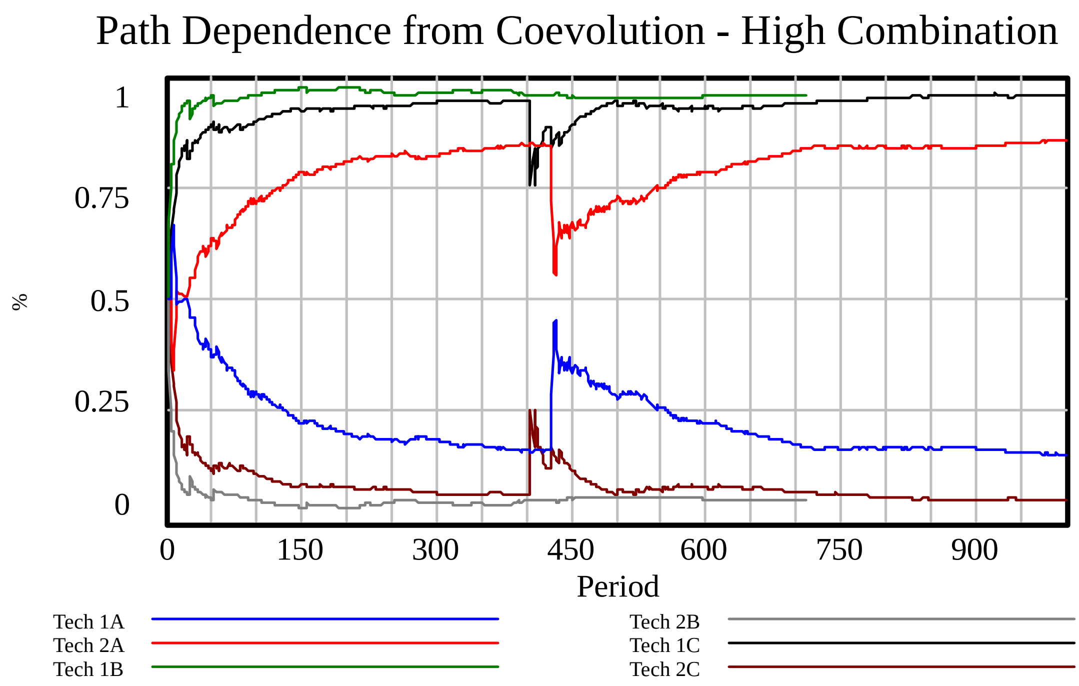


Figure 24. Points Where Long-Jump Events Occurred Causing Design Restart

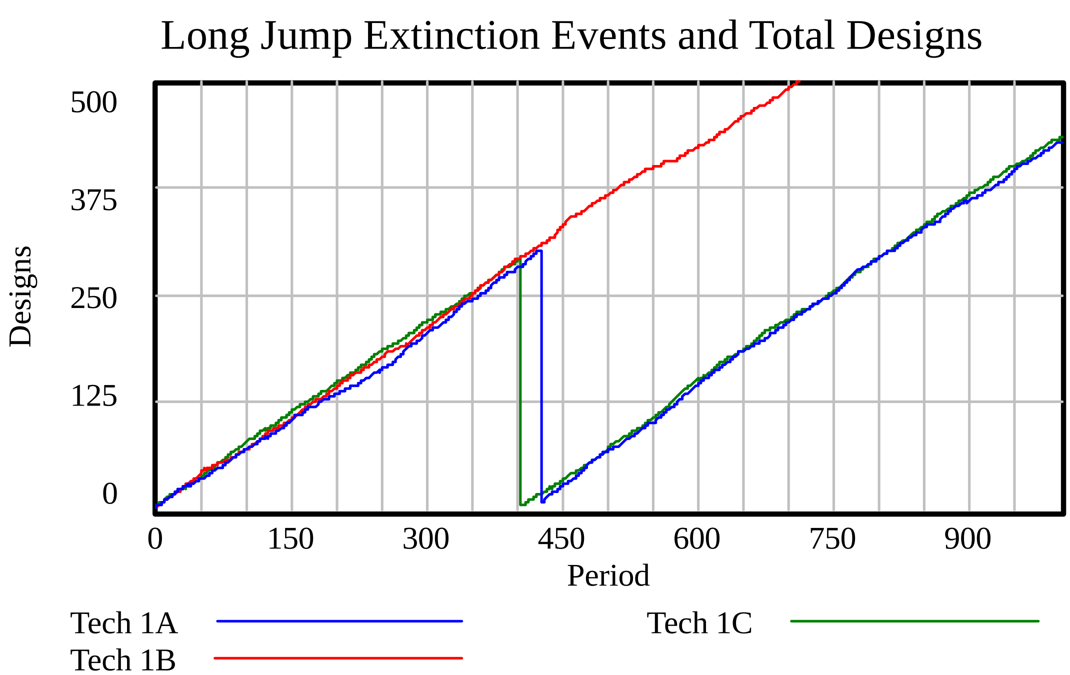


Figure 25. Effect of Coevolution on Path Dependence with 75% Extinction of Technology 1

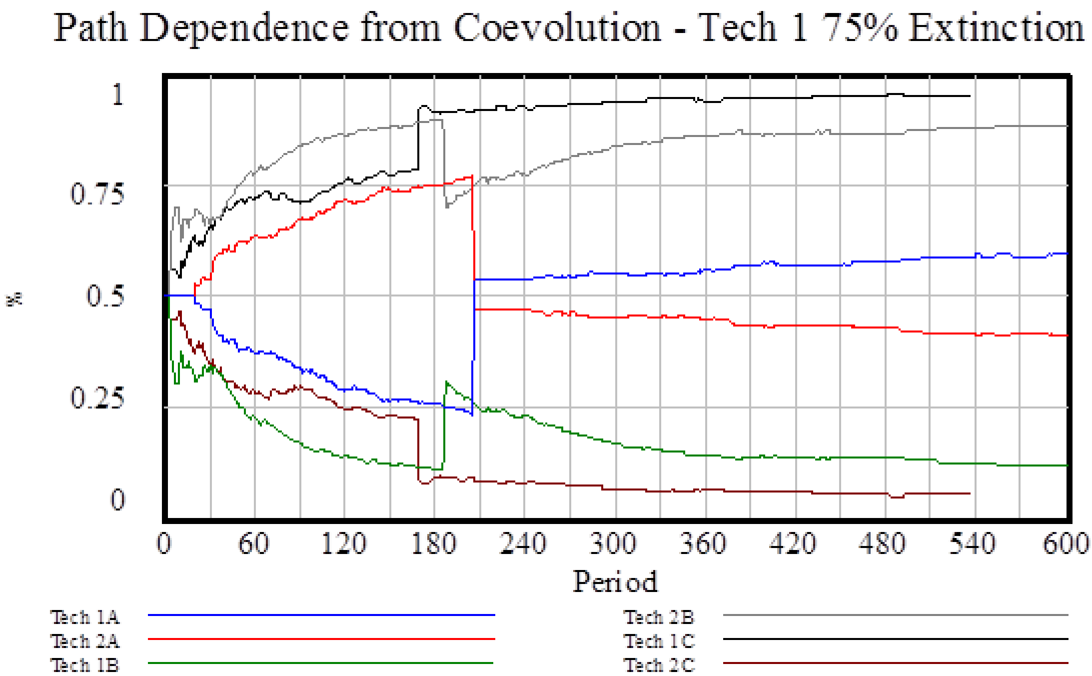
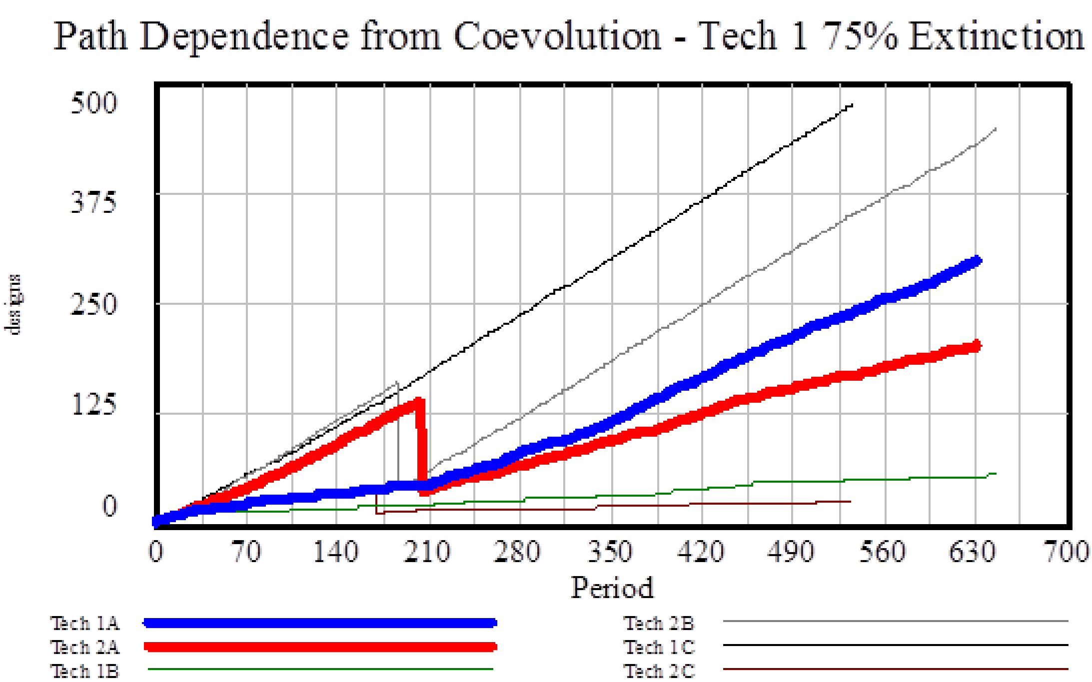


Figure 26. Cause of Crossover in Figure 23



Heavy lines show total good designs accepted during Run A. Even though technology 2 dominated good designs initially, the technology 1 extinction event was sufficient to change the proportion of each technology designs to slightly favor technology 1 and cause that technology to subsequently produce more designs than technology 2. The other technologies were less affected and no crossover occurred, though Run C showed similar effects as in Run A.

Figure 27. Effect of Feedback from High Test Failure Rate and Lock-in on Path Dependence

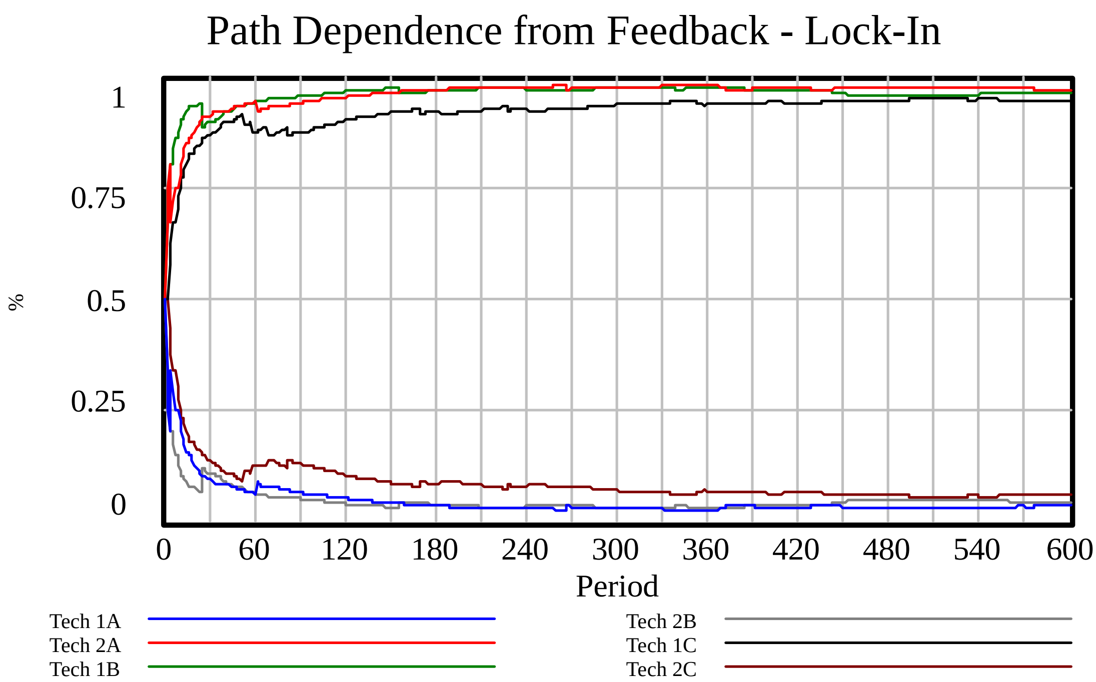


Figure 28. Effect of Feedback from High False Negative Rate and Lock-in on Path Dependence

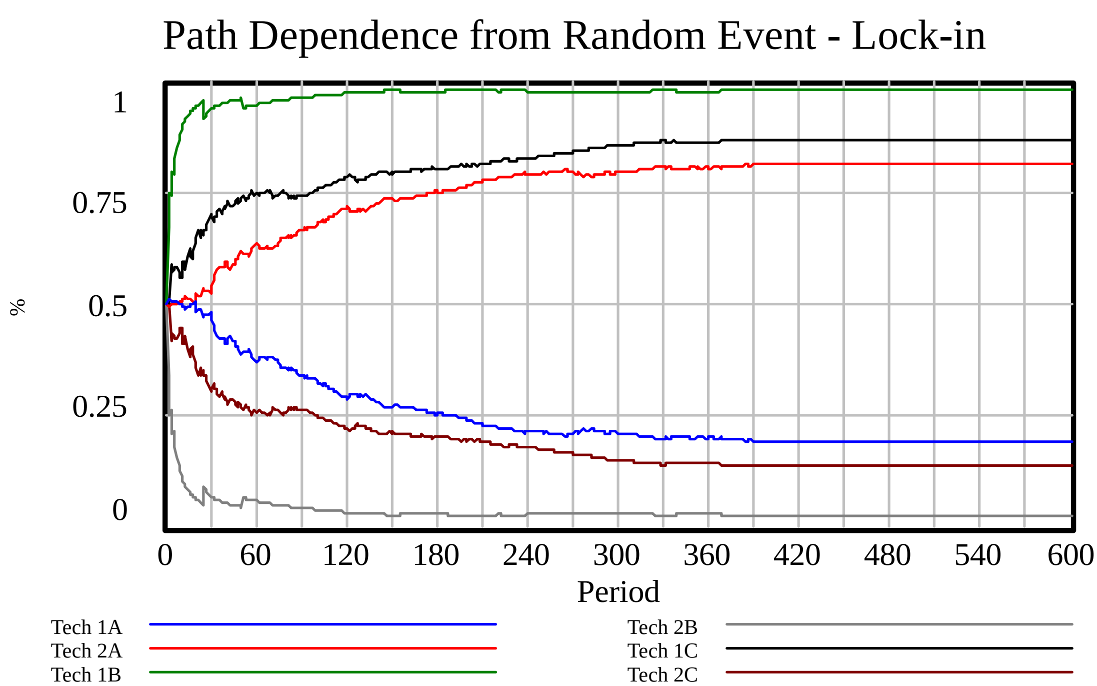
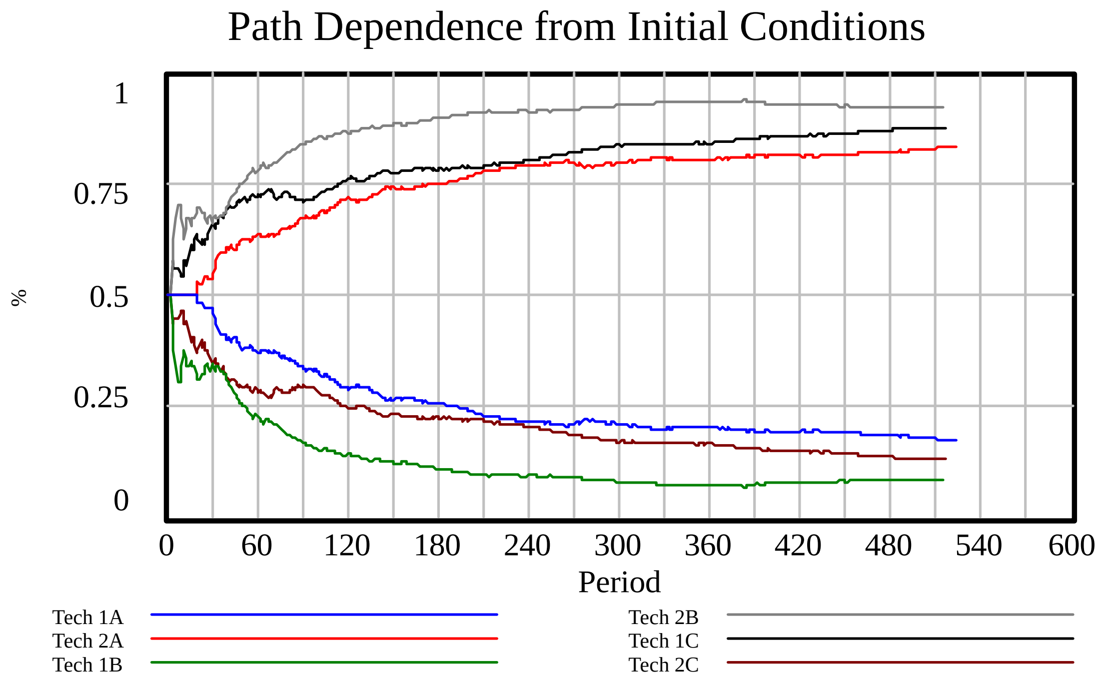


Figure 29. Effect of Initial Conditions on Path Dependence



A-5 System Dynamics Model Documentation

Development, Inspection/Test, and Extinction Activities

Add Extinction Event=Extinction Event*Key Delay
Units: Designs /period
Adds a generated extinction event to extinction count stock.

Completed Rework 1=Design 1 Rework/Rework 1 Delay
Units: Designs/period
Technology 1 design rework completed and placed in Good Design stock

Completed Rework 2=Design 2 Rework/Rework 2 Delay
Units: Designs/period
Technology 2 design rework completed and placed in Good Design stock

Design 1 Discovery Delay=10
Units: period
Average number of periods it takes to discover a technology 1 false negative design

Design 1 Failures=IF THEN ELSE (Technology 1 Design Selected = 1: AND: Technology 1 Design Accepted = 0, 1, 0)
Units: Designs/period
Number of selected technology designs rejected during test or inspection that are added to stock of technology 1 designs failed - nothing is added if technology 1 is selected

Design 1 Rework= INTEG (Rework 1 Added - Completed Rework 1, 0)
Units: Designs
Technology 1 Designs Awaiting Rework

Design 2 Discovery Delay=10
Units: period
Average number of periods it takes to discover a technology 2 false negative design

Design 2 Failures=IF THEN ELSE (Technology 2 Design Selected = 1: AND: Technology 2 Design Accepted = 0, 1, 0)
Units: Designs/period
Number of selected technology designs rejected during test or inspected that are added to stock of technology 2 designs failed - nothing is added if technology 2 is selected

Design 2 Rework= INTEG (Rework 2 Added - Completed Rework 2, 0)
Units: Designs
Technology 2 Designs Awaiting Rework

Design Delay=1
Units: period
Number of periods between new design generation

Designs Added Each Period=IF THEN ELSE ("Lock-in Notice" = 0: AND: (Technology 1 Good Designs + Technology 2 Good Designs)/Design Delay < Total Designs/Design Delay, 1, 0)
Units: Designs/period
The number of designs chosen per period, equal to one in the traditional model. If the total number of designs chosen equals the maximum number of designs to be generated, or a lock-in notice is active, the number of designs chosen per period goes to 0.

Event Delay=1
Units: period
Number of periods before extinction event added (always = 1)

Extinction 1 Draw=IF THEN ELSE (Extinction Count <= Max Extinctions, RANDOM UNIFORM(0,1,(Random Seed Input + 4500)),1)
Units: Dimensionless
Random Number to compare to probability of extinction to determine if technology 1 extinction will occur

Extinction 2 Draw=IF THEN ELSE(Extinction Count <= Max Extinctions, RANDOM UNIFORM(0,1,(Random Seed Input + 3500)),1)
Units: Dimensionless
Random Number to compare to probability of extinction to determine if technology 2 extinction will occur

Extinction Count= INTEG (Add Extinction Event, 1)
Units: Designs
Total number of extinction events generated during model run regardless of maximum number of extinctions generated. Extinction events generated only between extinction limits.

Extinction Delay=1
Units: period
Number of periods before extinction event takes place (always = 1)

Extinction Event= IF THEN ELSE(Extinction Switch = 1 :AND: (Extinction Lower Limit * Total Designs < Total Number of Designs) :AND: (Extinction Upper Limit * Total Designs > Total Number of Designs), 1 , 0)
Units: Dimensionless
If the extinction switch is on, and the total number of designs generated to date lies between the extinction lower and upper limits, the extinction event = 1 and the extinction event can occur, otherwise it is 0 and it will not occur

Extinction Lower Limit=0.01
Units: Dimensionless
Percent of total number of designs after which an extinction event is allowed to be generated

Extinction Switch=1
Units: Dimensionless
If = 1, extinction event can occur, if =0, extinction event cannot occur.

Extinction Upper Limit=0.5
Units: Dimensionless
Percent of the number of total designs beyond which extinction events no longer are allowed to be generated

False negative Design 1 Added=IF THEN ELSE (Technology 1 Design Accepted = 1, (1-Good Design 1 Added), 0)
Units: Designs/period
Number of false negative technology 1 designs added to the stock of false negative technology 1 designs if the technology 1 design is accepted, otherwise nothing is added

False negative Design 2 Added=IF THEN ELSE (Technology 2 Design Accepted = 1, (1-Good Design 2 Added), 0)
Units: Designs/period
Number of false negative technology 2 designs added to the stock of false negative technology 2 designs if the technology 2 design is accepted, otherwise nothing is added

FINAL TIME=IF THEN ELSE (Total Designs > Total Number of Designs, 2000, Total Designs) * Final Time Constant
Units: period
The final time for the simulation.

Final Time Delay=1
Units: period/Designs
Number of designs delayed for final time to occur

Good Design 1 Added=Technology 1 Design Accepted * IF THEN ELSE (Tech 1 Accept Draw <= Good Design 1 Probability, 1, 0)
Units: Designs/period
Number of good technology 1 designs plus reworked false negative technology 1 designs added to the stock of good technology 1 designs

Good Design 1 Adjustment=IF THEN ELSE(Technology 1 Extinction/Extinction Delay = 1, (Technology 1 Good Designs* Percent Extinction/Extinction Delay) -1, 0)
Units: Designs/period
If extinction occurs, designated percent of good technology 1 designs are removed from the stock and design sequence continues with remaining designs (if any)

Good Design 1 Probability=0.9
Units: Dimensionless
Fraction of accepted technology 1 designs that do not have false negative test or inspection results

Good Design 2 Added=Technology 2 Design Accepted * IF THEN ELSE (Tech 2 Accept Draw <= Good Design 2 Probability, 1, 0)
Units: Designs/period
Number of good technology 2 designs plus reworked false negative technology 2 designs added to the stock of good technology 2 designs

Good Design 2 Adjustment=IF THEN ELSE(Technology 2 Extinction/Extinction Delay = 1, (Technology 2 Good Designs* Percent Extinction/Extinction Delay) -1, 0)
Units: Designs/period
If extinction occurs, designated percent of good technology 1 designs are removed from the stock and design sequence continues with remaining designs (if any

Good Design 2 Probability=0.9
Units: Dimensionless
Fraction of accepted technology 2 designs that do not have false negative test or inspection results

Initial Probability of Choosing Technology 1=1
Units: Dimensionless
Exogenous variable that establishes the probability of Technology 1 being initially chosen. The default value is 0.5

Initial Technology 1 Designs=1
Units: Designs
There is one unit of technology 1 in the technology 1 stock. This can be increased to increase the probability that a technology 1 unit will be selected in the first period.

Initial Technology 2 Designs=1
Units: Designs
There is one unit of technology 2 in the technology 2 stock. This can be increased to increase the probability that a technology 2 unit will be selected in the first period.

"Lock-in Notice"=IF THEN ELSE("Lock-in Switch" = 1, “Cost Lock-In Occurrence" + "Schedule Lock-in Occurrence", 0)
Units: Dimensionless
Activates a lock-in notice if the lock-in switch is on and cost or schedule lock-in occurs

"Lock-in Switch"=0
Units: Designs/period
If = 1, schedule or cost lock-in will stop designs from being generated, if = 0, lock-in will have no effect

Max Extinctions=1
    Units: Designs/period
    Total number of extinction events allowed in a single model run

Percent Extinction=0.75
    Units: Dimensionless
    Percent of good designs to be removed from stock during extinction event

Probability of Choosing Technology 1=IF THEN ELSE (Time = 0, Initial Probability of Choosing Technology 1, 1/(1+exp (-Sensitivity to Proportion*(Proportion of Technology 1 Designs - 0.5))))
    Units: Dimensionless
    The probability of choosing technology 1 is a function of the proportion of technology 1 choices. The exponential function is used. The probability of choosing technology 1 is 1/2 when the proportion of technology1 is 1/2.

Probability of Choosing Technology 2=IF THEN ELSE (Time = 0, (1-Initial Probability of Choosing Technology 1), 1/(1+exp (-Sensitivity to Proportion *(Proportion of Technology 2 Units -0.5))))
    Units: Dimensionless
    The probability of choosing technology 2 is a function of the proportion of technology 2 choices. The exponential function is used. The probability of choosing technology 2 is 1/2 when the proportion of technology 2 is 1/2.

Proportion of Technology 1 Designs=(Technology 1 False negative Designs + Technology 1 Good Designs)/Total Number of Designs
    Units: Dimensionless
    The proportion of technology 1 choices.

Proportion of Technology 2 Designs=(Technology 2 False negative Designs + Technology 2 Good Designs)/Total Number of Designs
    Units: Dimensionless
    The proportion of technology 2 choices.

Random Draw=RANDOM UNIFORM (0,1,Random Seed Input)
    Units: Dimensionless
    Each period a random number is drawn from the uniform distribution on the interval [0, 1].

Random Seed Input= 1614
    Units: Dimensionless
    Exogenous variable that triggers other Random Number Seeds

Rework 1 Added=Technology 1 False negative Designs/Design 1 Discovery Delay
Units: Designs/period
Number of technology 1 false negative designs moved from the false negative design stock to the rework stock

Rework 1 Delay=4
Units: period
Average number of periods it takes to rework a technology 1 false negative design

Rework 2 Added=Technology 2 False negative Designs/Design 2 Discovery Delay
Units: Designs/period
Number of technology 2 false negative designs moved from the false negative design stock to the rework stock

Rework 2 Delay=5
Units: period
Average number of periods it takes to rework a technology 2 false negative design

Sensitivity to Proportion=7
Units: Dimensionless
The larger this parameter, the faster the probability of choosing a given technology increases with its proportion of total technologies selected.

Tech 1 Accept Draw=RANDOM UNIFORM (0,1, (Random Seed Input + 1800))
Units: Dimensionless
Random number generation to determine if inspection or test result of an accepted design is a false negative (should have been a rejection).

Tech 1 Failure Draw=RANDOM UNIFORM (0,1, (Random Seed Input + 1600))
Units: Dimensionless
Random number generation to determine if design is rejected during inspection or test.

Tech 2 Accept Draw=RANDOM UNIFORM (0,1, (Random Seed Input + 2200))
Units: Dimensionless
Random number generation to determine if inspection or test result of an accepted design is a false negative (should have been a rejection).

Tech 2 Failure Draw=RANDOM UNIFORM (0,1, (Random Seed Input + 2000))
Units: Dimensionless
Random number generation to determine if design is rejected during inspection or test.

Technology 1 Design Accepted=Technology 1 Design Selected * IF THEN ELSE (Tech 1 Failure Draw > Technology 1 Failure Probability, 1, 0)
Units: Designs/period
Accepts a tested or inspected technology 1 design if the random draw is less than the probability of technology 1 passing the test or inspection

Technology 1 Design Quality=Technology 1 Good Designs/(Technology 1 False negative Designs + Technology 1 Good Designs + Total Technology 1 Designs Failed)

Units: Dimensionless

The ratio of total good technology 1 designs to total technology 1 designs tested or inspected - does not include reworked designs

Technology 1 Design Selected=Designs Added Each Period * IF THEN ELSE (Random Draw <=Probability of Choosing Technology 1, 1, 0)

Units: Designs/period

Adds a design from technology 1 if the random draw is less than or equal to the probability of selecting a technology 1 design

Technology 1 Extinction=IF THEN ELSE(Extinction 1 Draw < Technology 1 Probability of Extinction, Extinction Event, 0)

Units: Designs

Causes a technology 1 extinction event to occur if the extinction 2 random number is less than the probability of the extinction occurring

Technology 1 Failure Probability=0.1

Units: Dimensionless

Exogenous variable that establishes the probability of a technology 1 unit passing inspection or test.

Technology 1 False negative Designs=INTEG (False negative Design 1 Added - Rework 1 Added, 0)

Units: Designs

Stock of total false negative technology 1 designs that have not been detected and have not been reworked

Technology 1 Good Designs=INTEG (Completed Rework 1 + Good Design 1 Added - Good Design 1 Adjustment, Initial Technology 1 Designs)

Units: Designs

Total number of good technology 1 designs

Technology 1 Probability of Extinction=0

Units: Dimensionless

Probability that technology 1 extinction will occur

Technology 2 Design Accepted=Technology 2 Design Selected * IF THEN ELSE (Tech 2 Failure Draw > Technology 2 Failure Probability, 1, 0)

Units: Designs/period

Accepts a tested or inspected technology 2 design if the random draw is less than the probability of technology 2 passing the test or inspection

Technology 2 Design Quality=Technology 2 Good Designs/(Technology 2 False negative Designs + Technology 2 Good Designs + Total Technology 2 Designs Failed)

Units: Dimensionless

The ratio of total good technology 2 designs to total technology 2 designs tested or inspected - does not include reworked designs

Technology 2 Design Selected=Designs Added Each Period * IF THEN ELSE (Random Draw <=Probability of Choosing Technology 2, 1, 0)

Units: Designs/period

Adds a design from technology 2 if the random draw is less than or equal to the probability of selecting a technology 2 design

Technology 2 Extinction=IF THEN ELSE(Extinction 2 Draw <Technology 2 Probability of Extinction, Extinction Event, 0)

Units: Designs

Causes a technology 2 extinction event to occur if the extinction 2 random number is less than the probability of the extinction occurring

Technology 2 Failure Probability=0.1

Units: Dimensionless

Exogenous variable that establishes the initial probability of a technology 2 unit passing inspection or test.

Technology 2 False negative Designs= INTEG (False negative Design 2 Added-Rework 2 Added, 0)

Units: Designs

Stock of total false negative technology 2 designs that have not been detected and have not been reworked

Technology 2 Good Designs= INTEG (Completed Rework 2 + Good Design 2 Added - Good Design 2 Adjustment, Initial Technology 2 Designs)

Units: Designs

Total number of good technology 2 designs

Technology 2 Probability of Extinction=0.01

Units: Dimensionless

Probability that technology 2 extinction will occur

Total Design Quality=(Technology 1 Good Designs + Technology 2 Good Designs)/(Technology 1 False negative Designs + Technology 1 Good Designs +Total Failures + Technology 2 False negative Designs + Technology 2 Good Designs)

Units: Dimensionless

The ratio of total good designs to total designs tested or inspected - does not include reworked designs

Total Designs=500
Units: Designs
The total number of accepted technology units required to complete the design phase.

Total Failures=Total Technology 1 Designs Failed + Total Technology 2 Designs Failed
Units: Designs
Cumulative number of failed technology 1 and 2 designs

Total Number of Designs=Technology 1 False negative Designs + Technology 1 Good Designs + Technology 2 False negative Designs + Technology 2 Good Designs
Units: Designs
The total number of units added from both technologies, including good designs and false negative accepted designs

Total Technology 1 Designs Failed= INTEG (Design 1 Failures, 0)
Units: Designs
The total number of technology 1 designs units that have failed inspection or test

Total Technology 2 Designs Failed= INTEG (Design 2 Failures, 0)
Units: Designs
The total number of technology 2 designs units that have failed inspection or test

Cost and Schedule Activities

"Cost %"=Cost Table (Total Number of Designs)
Units: Dimensionless
The percent of maximum cost from the cost table that will be used to determine redesign, design development, test or inspection, or rework cost for the period

Average Days Per Design=1.6
Units: Days/Designs
Average days required to complete each design

Completed Rework 1=Design 1 Rework/Rework 1 Delay
Units: Designs/period
Technology 1 design rework completed and placed in Good Design stock

Completed Rework 2=Design 2 Rework/Rework 2 Delay
Units: Designs/period
Technology 2 design rework completed and placed in Good Design stock

"Cost Lock-In Occurrence"= IF THEN ELSE (Total Cumulative Cost/Maximum Allowed Cost < 1, 0, 1)
Units: Dimensionless
If maximum allowed cost is exceeded, lock-in occurs

Cost Table ([(0,0)-1000,1),(0,0),(100,0.0394737),(200,0.0657895),(300,0.122807),(400,0.184211),(500,0.254386),(600,0.42),(700,0.6),(800,0.8),(900,0.95),(1000,1),(5000,1),(5000,1)],(0,0),(64.2202,0.0175439),(128.44,0.0438596),(192.661,0.0701754),(250.765,0.0921053),(308.868,0.122807),(373.089,0.166667),(431.193,0.20614),(498.471,0.263158),(556.575,0.346491),(617.737,0.429825),(691.131,0.552632),(749.235,0.679825),(795.107,0.780702),(844.037,0.868421),(883.792,0.938596),(938.838,0.969298),(1000,1))
Units: Dimensionless
Percent of maximum cost to be applied during each period

Cumulative Design Cost= INTEG (Design Cost Added, 0)
Units: Dollars
Cumulative amount of Unit Cost up to and including the current period.

Cumulative Redesign Cost= INTEG (Redesign Cost Added, 0)
Units: Dollars
Cumulative amount of redesign cost, up to and including the current period.

Cumulative Rework Cost= INTEG (Rework Cost Added, 0)
Units: Dollars
Cumulative amount of rework cost, up to and including the current period.

Cumulative Test Cost= INTEG (Test Cost Added, 0)
Units: Dollars
Cumulative amount of test and inspection cost, up to and including the current period.

Design 1 Failures=IF THEN ELSE (Technology 1 Design Selected = 1: AND: Technology 1 Design Accepted = 0, 1, 0)
Units: Designs/period
Number of rejected technology 1 designs added to stock of technology 1 designs failed

Design 2 Failures=IF THEN ELSE (Technology 2 Design Selected = 1: AND: Technology 2 Design Accepted = 0, 1, 0)
Units: Designs/period
Number of selected technology designs rejected during test or inspected that are added to stock of technology 2 designs failed - nothing is added if technology 2 is selected

Design Cost=MAX ((Technology 1 Design Accepted + Technology 2 Design Accepted), 0)* Max Design Cost * "Cost %"
Units: Dollars/period
Cost of a unit development. Determined by multiplying the maximum unit development cost by the cost %.

Design Cost Added=Design Cost
Units: Dollars/period
Dollar amount added each period to the Cumulative Unit Cost stock

Designs Selected=Technology 1 Design Selected + Technology 2 Design Selected
Units: Designs/period
Total number of designs added each period

"Lock-in Notice"=IF THEN ELSE ("Lock-in Switch" = 1, "Cost Lock-In Occurrence" + "Schedule Lock-in Occurrence", 0)
Units: Dimensionless
Activates a lock-in notice if the lock-in switch is on and cost or schedule lock-in occurs

"Lock-in Switch"=0
Units: Dimensionless
If = 1, schedule or cost lock-in will stop designs from being generated, if = 0, lock-in will have no effect.

Max Design Cost=20000
Units: Dollars/Designs
Exogenous variable. The most dollars that a single unit development will cost

Max Redesign Cost=25000
Units: Dollars/Designs
Exogenous variable. The most dollars that a single redesign will cost

Max Rework Cost=25000
Units: Dollars/Designs
Exogenous variable. The most dollars that a single rework will cost

Max Test Cost=10000
Units: Dollars/Designs
Exogenous variable. The most dollars that a single test or inspection will cost

Maximum Allowed Cost=100,000
Units: Dollars
Budget Limit for Design - above which lock-in occurs

Maximum Days Allowed=1000
Units: Days
Total days budgeted to complete all designs

Redesign Cost=MAX ((Design 1 Failures + Design 2 Failures), 0) * Max Redesign Cost * "Cost %"
Units: Dollars/period
Cost of redesign of a unit that failed test or inspection. Determined by multiplying the maximum redesign cost by the cost %. If no unit failed, there is no cost.

Redesign Cost Added=Redesign Cost
Units: Dollars/period
Dollar amount added each period to the Cumulative Redesign Cost stock

Rework Cost=MAX ((Completed Rework 1 + Completed Rework 2), 0) * Max Rework Cost * "Cost %"
Units: Dollars/period
Cost of rework of a design that tested or inspected as a false negative and was later discovered to be a failure. Determined by multiplying the maximum rework cost by the cost %. If no unit was reworked, there is no cost.

Rework Cost Added= Rework Cost
Units: Dollars/period
Dollar amount added each period to the Cumulative Rework Cost stock

"Schedule Lock-in Occurrence"=IF THEN ELSE (Total Days Expended/Maximum Days Allowed < 1, 0, 1)
Units: Dimensionless
If maximum allowed schedule is exceeded, lock-in occurs

Technology 1 Design Accepted=Technology 1 Design Selected * IF THEN ELSE (Tech 1 Failure Draw > Technology 1 Failure Probability, 1, 0)
Units: Designs/period
Accepts a tested or inspected technology 1 design if the random draw is less than the probability of technology 1 passing the test or inspection

Technology 1 Design Selected=Designs Added Each Period * IF THEN ELSE (Random Draw <=Probability of Choosing Technology 1, 1, 0)

Units: Designs/period

Adds a design from technology 1 if the random draw is less than or equal to the probability of selecting a technology 1 design

Technology 2 Design Accepted=Technology 2 Design Selected * IF THEN ELSE Tech 2 Failure Draw > Technology 2 Failure Probability, 1, 0)

Units: Designs/period

Accepts a tested or inspected technology 2 design if the random draw is less than the probability of technology 2 passing the test or inspection

Technology 2 Design Selected=Designs Added Each Period * IF THEN ELSE (Random Draw <=Probability of Choosing Technology 2, 1, 0)

Units: Designs/period

Adds a design from technology 2 if the random draw is less than or equal to the probability of selecting a technology 2 design

Test Cost=MAX ((Technology 1 Design Selected + Technology 2 Design Selected), 0) * Max Test Cost * "Cost %"

Units: Dollars/period

Cost of an inspection or test. Determined by multiplying the maximum test cost by the cost %.

Test Cost Added=Test Cost

Units: Dollars/period

Dollar amount added each period to the Cumulative Test Cost stock

Total Cumulative Cost=Cumulative Redesign Cost + Cumulative Rework Cost + Cumulative Test Cost + Cumulative Design Cost

Units: Dollars

Total cumulative cost for designs

Total Days Expended=Total Designs Selected * Average Days Per Design

Units: Days

Total number of days required to perform all work up to this time

Total Designs Selected= INTEG (Designs Selected, 0)

Units: Designs

Cumulative designs selected

Total Number of Designs=Technology 1 False negative Designs + Technology 1 Good Designs + Technology 2 False negative Designs + Technology 2 Good Designs

Units: Designs

The total number of units added from both technologies, including good designs and false negative accepted design

Appendix B – Data Envelopment Analysis

B-1 Supporting Data for Data Tables

The Comparison of Model vs. Actual Results table on the following page reflects DEA scores and ranking of DMUs for all projects evaluated for fiscal years 2005, 2006, and 2007. The blue DMUs were the projects selected for funding by the evaluation team. The DEA model used the same evaluation criteria as the evaluation team.

The Project Selection Using Minimum Affordability Parameters table on the following page reflects DEA scores using six final affordability fitness variables to evaluate the same input data as in the previous table. Again, the blue DMUs were the projects selected for funding by the evaluation team. The red DMUs were rated as efficient, but reflect slack, which means excess inputs or shortfalls in output were encountered.

Table 15. Comparison Using Traditional Evaluation Criteria

COMPARISON OF MODEL VS. ACTUAL RESULTS USING CCRI DEA MODEL

FY05 Facilities

No.	DMU	Score
3	F-114	1
5	**F-116**	1
7	**F-222**	1
8	**F-223**	1
15	**F-313**	1
19	**F-317**	1
24	**F-322**	1
6	**F-221**	0.980482
13	**F-311**	0.958141
20	**F-318**	0.892346
21	**F-319**	0.883444
22	**F-320**	0.87411
16	**F-314**	0.732657
23	**F-321**	0.648667
4	F-115	0.441002
17	F-315	0.398804
10	F-225	0.383186
2	F-113	0.301396
1	F-112	0.296207
18	F-316	0.232893
14	F-312	0.223041
9	F-224	0.182896
11	F-226	0.178299
12	**F-229**	0.176414

FY06 Facilities

No.	DMU	Score
3	**FAR01**	1
5	**FAR03**	1
17	**FAR15**	1
25	FNV02	1
29	**FNV06**	1
30	**FNV07**	1
35	FNV12	1
36	**FNV13**	1
4	**FAR02**	0.891625
13	**FAR11**	0.888889
18	**FAR16**	0.888889
15	**FAR13**	0.882943
24	**FNV01**	0.867027
23	**FAR21**	0.830979
6	**FAR04**	0.799887
22	**FAR20**	0.798417
28	FNV05	0.632338
32	FNV09	0.567685
12	FAR10	0.516043
31	FNV08	0.449179
26	FNV03	0.449146
7	FAR05	0.444426
14	FAR12	0.428403
37	FNV14	0.38181
33	FNV10	0.304413
34	FNV11	0.25698
9	FAR07	0.225288
19	FAR17	0.190466
11	FAR09	0.167799
8	FAR06	0.152996
20	FAR18	0.152996
27	**FNV04**	0.152118
10	FAR08	0.147946
21	FAR19	0.119843
16	FAR14	0.115964
1	FAF01	6.03E-02
2	FAF02	6.03E-02

FY07 Facilities

No.	DMU	Score
2	FAR02	1
3	**FAR03**	1
7	**FAR07**	1
10	**FAR10**	1
15	**FAR15**	1
28	FNV02	1
30	**FNV04**	1
17	**FAR17**	0.962484
5	**FAR05**	0.912243
8	**FAR08**	0.901907
19	**FAR19**	0.895669
1	**FAR01**	0.875518
20	FAR20	0.859735
33	**FNV07**	0.843257
27	FNV01	0.80646
22	FAR22	0.783784
18	FAR18	0.78125
34	FNV08	0.766499
24	FAR24	0.680981
21	FAR21	0.651988
32	FNV06	0.623727
29	**FNV03**	0.595056
9	FAR09	0.547631
16	FAR16	0.511254
11	FAR11	0.475141
31	FNV05	0.393285
4	FAR04	0.351684
23	FAR23	0.303742
13	FAR13	0.300967
14	FAR14	0.264598
6	FAR06	0.251918
12	FAR12	0.251918
25	FAR26	0.218849
26	FAR27	0.218631

FY05 Weapons

No.	DMU	Score
2	W-102	1
3	W-103	1
5	W-105	1
7	**W-107**	1
9	W-109	1
27	**W-215**	1
35	**W-303**	1
41	**W-309**	1
30	W-218	0.975829
6	W-106	0.965676
31	W-219	0.956131
26	**W-214**	0.946912
37	**W-305**	0.938977
24	**W-212**	0.859265
33	W-301	0.814095
29	W-217	0.805292
1	**W-101**	0.784732
28	**W-216**	0.713732
12	**W-117**	0.709827
32	W-220	0.650385
36	W-304	0.615743
20	**W-208**	0.60562
34	W-302	0.514946
4	W-104	0.514584
23	**W-211**	0.445565
17	W-205	0.40897
11	W-111	0.407177
8	W-108	0.388011
15	**W-203**	0.371713
16	W-204	0.350573
38	W-306	0.329948
39	W-307	0.329948
10	W-110	0.289174
19	W-207	0.286985
22	W-210	0.28177
21	W-209	0.279908
14	W-202	0.226746
25	W-213	0.199372
18	W-206	0.199263
13	**W-201**	0.148236
40	W-308	0.143223

FY06 Weapons

No.	DMU	Score
1	**WAF01**	1
2	**WAF02**	1
3	**WAF03**	1
4	**WAF04**	1
7	**WAF07**	1
9	**WAF09**	1
10	WAF10	1
21	WAR11	1
23	**WNA01**	1
25	**WNA03**	1
27	**WNA05**	1
33	**WNA19**	1
41	**WNS18**	1
26	WNA04	0.954115
17	**WAR07**	0.888889
34	**WNS11**	0.857143
22	**WAR12**	0.841258
29	WNA07	0.640323
35	WNS12	0.595929
18	WAR08	0.449102
38	WNS15	0.423987
8	WAF08	0.284088
14	WAR04	0.252101
31	WNA09	0.237991
30	WNA08	0.227758
37	WNS14	0.216645
32	WNA10	0.178278
28	WNA06	0.15366
36	WNS13	0.150026
24	WNA02	0.133333
5	WAF05	0.131033
13	WAR03	0.124993
15	WAR05	0.124993
19	WAR09	0.124993
12	WAR02	0.111111
39	WNS16	0.111111
6	WAF06	0.10762
40	WNS17	0.103348
20	WAR10	8.29E-02
16	WAR06	7.60E-02
11	WAR01	6.69E-02

FY07 Weapons

No.	DMU	Score
1	WAF01	1
6	**WAF06**	1
7	WAF07	1
8	WAR01	1
14	WDD01	1
21	**WNA03**	1
22	**WNA04**	1
26	**WNS02**	1
31	**WNS07**	1
4	**WAF04**	0.960878
25	**WNS01**	0.929782
11	**WAR04**	0.809354
10	WAR03	0.794734
16	**WMC02**	0.763322
2	WAF02	0.696171
29	**WNS05**	0.688991
30	WNS06	0.685804
32	**WNS08**	0.673157
3	WAF03	0.662776
13	**WAR06**	0.662776
5	WAF05	0.609008
17	WMC03	0.572209
20	WNA02	0.502731
24	WNA06	0.464524
27	WNS03	0.463486
12	WAR05	0.403603
23	WNA05	0.3125
28	WNS04	0.26756
15	WMC01	0.187862
33	WNS09	0.184753
18	WMC04	0.177391
35	WNS11	0.11761
9	WAR02	0.111111
19	WNA01	0.11084
34	WNS10	0.103027

Selected projects in blue

Table 16. Comparison Using Affordability Evaluation Criteria

PROJECT SELECTION USING MINIMUM AFFORDABILITY PARAMETERS IN CCRI DEA MODEL

FY05 Facilities

No.	DMU	Score
3	F-114	1
5	**F-116**	1
7	**F-222**	1
8	**F-223**	1
10	F-225	1
16	**F-314**	1
18	F-316	1
24	**F-322**	1
14	F-312	1
17	F-315	1
20	**F-318**	0.993265
21	**F-319**	0.955821
13	**F-311**	0.901879
15	**F-313**	0.895944
22	**F-320**	0.888851
23	**F-321**	0.871169
12	**F-229**	0.77026
19	**F-317**	0.745535
6	**F-221**	0.694191
11	F-226	0.5
1	F-112	0.4
4	F-115	0.276199
9	F-224	0.228678
2	F-113	0.155791

FY06 Facilities

No.	DMU	Score
3	**FAR01**	1
5	**FAR03**	1
17	**FAR15**	1
18	**FAR16**	1
23	**FAR21**	1
25	FNV02	1
26	FNV03	1
28	FNV05	1
29	**FNV06**	1
35	FNV12	1
36	**FNV13**	1
13	**FAR11**	1
15	**FAR13**	0.985161
6	**FAR04**	0.950182
24	**FNV01**	0.897545
22	**FAR20**	0.893648
4	**FAR02**	0.891625
30	**FNV07**	0.888889
16	FAR14	0.888889
20	FAR18	0.888889
12	FAR10	0.888889
27	**FNV04**	0.878505
19	FAR17	0.820017
7	FAR05	0.76748
9	FAR07	0.760523
32	FNV09	0.726495
21	FAR19	0.714286
37	FNV14	0.702083
31	FNV08	0.66453
8	FAR06	0.629706
10	FAR08	0.623955
14	FAR12	0.619642
33	FNV10	0.518812
1	FAF01	0.5
2	FAF02	0.5
34	FNV11	0.383232
11	FAR09	0.218565

FY07 Facilities

No.	DMU	Score
2	FAR02	1
3	**FAR03**	1
7	**FAR07**	1
10	**FAR10**	1
13	FAR13	1
14	FAR14	1
15	**FAR15**	1
17	**FAR17**	1
18	FAR18	1
19	**FAR19**	1
20	FAR20	1
31	FNV05	1
32	FNV06	1
23	FAR23	0.9552
1	**FAR01**	0.943744
29	**FNV03**	0.940507
21	FAR21	0.93292
8	**FAR08**	0.92378
5	FAR05	0.916402
12	FAR12	0.912722
33	FNV07	0.90293
34	FNV08	0.864336
4	FAR04	0.829222
16	FAR16	0.809524
30	FNV04	0.809524
27	FNV01	0.80646
25	FAR26	0.763636
26	FAR27	0.763636
24	FAR24	0.583973
11	FAR11	0.577934
22	FAR22	0.509907
9	FAR09	0.505952
6	FAR06	0.502234
28	FNV02	0.49646

FY05 Weapons

No.	DMU	Score
1	**W-101**	1
2	W-102	1
3	W-103	1
7	**W-107**	1
9	W-109	1
12	**W-117**	1
26	**W-214**	1
35	**W-303**	1
41	**W-309**	1
27	**W-215**	0.991913
28	**W-216**	0.985125
20	**W-208**	0.915741
24	**W-212**	0.8896
23	**W-211**	0.86537
37	**W-305**	0.789776
32	W-220	0.777622
6	W-106	0.671163
15	**W-203**	0.583737
13	**W-201**	0.496394
36	W-304	0.388576
5	W-105	0.327327
22	W-210	0.270029
29	W-217	0.25985
11	W-111	0.256117
8	W-108	0.248155
25	W-213	0.24003
14	W-202	0.215324
31	W-219	0.211653
30	W-218	0.208746
16	W-204	0.198361
18	W-206	0.195801
4	W-104	0.190729
34	W-302	0.190677
10	W-110	0.186695
17	W-205	0.150739
33	W-301	0.141722
38	W-306	0.117561
21	W-209	0.10824
39	W-307	0.107572
19	W-207	9.85E-02
40	W-308	7.90E-02

FY06 Weapons

No.	DMU	Score
1	**WAF01**	1
2	**WAF02**	1
3	**WAF03**	1
4	**WAF04**	1
8	WAF08	1
9	**WAF09**	1
10	WAF10	1
13	WAR03	1
15	WAR05	1
17	**WAR07**	1
18	WAR08	1
19	WAR09	1
21	WAR11	1
24	WNA02	1
27	**WNA05**	1
28	WNA06	1
30	WNA08	1
31	WNA09	1
41	**WNS18**	1
25	**WNA03**	1
12	WAR02	1
26	WNA04	0.963354
7	**WAF07**	0.911078
33	**WNA19**	0.861466
34	**WNS11**	0.857143
36	WNS13	0.846395
22	**WAR12**	0.773617
40	WNS17	0.676045
5	WAF05	0.670114
39	WNS16	0.666667
23	**WNA01**	0.594951
35	WNS12	0.582679
11	WAR01	0.504302
29	WNA07	0.497974
38	WNS15	0.423987
6	WAF06	0.40121
37	WNS14	0.384542
32	WNA10	0.383366
14	WAR04	0.357724
16	WAR06	0.193502
20	WAR10	5.69E-02

FY07 Weapons

No.	DMU	Score
1	WAF01	1
2	WAF02	1
3	WAF03	1
5	WAF05	1
6	**WAF06**	1
8	WAR01	1
13	**WAR06**	1
14	WDD01	1
15	WMC01	1
26	**WNS02**	1
29	**WNS05**	1
31	**WNS07**	1
22	**WNA04**	0.965076
19	WNA01	0.963819
18	WMC04	0.943529
25	**WNS01**	0.929782
21	**WNA03**	0.902707
35	WNS11	0.8
7	WAF07	0.768893
10	WAR03	0.727273
20	WNA02	0.725621
23	WNA05	0.717447
11	**WAR04**	0.717043
4	**WAF04**	0.645128
30	WNS06	0.625
32	**WNS08**	0.567554
24	WNA06	0.5
17	WMC03	0.5
16	**WMC02**	0.46875
28	WNS04	0.375
12	WAR05	0.3125
27	WNS03	0.3125
9	WAR02	0.307741
33	WNS09	0.244115
34	WNS10	0.239448

Selected projects in blue
Efficient projects with slack variables in red

B-2 Department of Defense Corrosion R&D Program Project Selection Using DEA FY2008 to FY2012

The Department of Defense ran the fiscal year 2008 evaluation using DEA in parallel with the manual process used by the evaluation team. The team provided inputs for some DEA affordability fitness variables. The following two pages show the FY 2008 actual input data forms and Vensim DSSP software model output for weapon systems projects on the first page and for facilities and infrastructure projects on the second page. The blue DMUs in the DEA Output Data table reflect those projects selected for funding.

Data for the next three years (FY 2009 to 2011) are found on the six pages, following the FY 2008 results, and contain the same data in the same format. In those years, DEA was used as the primary data source, with adjustments to the DEA ranking performed by the evaluation team after reviewing the DEA results and the project contents. Note that beginning in FY 2010, Cost of Corrosion replaced the Acceptance Index as an input to the DEA model.

Data for FY 2012 are complete and are shown on the final two pages of DEA results. Weapon systems and facilities projects were evaluated using a single DEA model run. The results are shown in the same format as the other tables. However, final selection was dependent on the availability funding as of this writing, so the actual projects funded were not yet known. However, funding was to be applied in the order of blue DMUs shown.

Table 17. FY08 Weapon System DEA Results

Red Column Headings Indicate Input Data

DMU	(O) ROI	$K Savings	Service	OSD	(I) % OSD	(I) Perform Period	(O) Accept Index	(O) Joint Index	Readiness Benefits Index	Logistics Benefits Index	Safety Benefits Index	(O) Total Benefits Index
W08AF01	24.4	9761	100	300	0.75	12	3.67	5.00	1.00	1.33	2.00	4.33
W08AF05	113.1	42428	125	250	0.67	12	2.67	4.67	2.00	1.67	5.00	8.67
W08AF07	23.49	8221	100	250	0.71	12	2.00	3.00	1.00	1.67	2.00	4.67
W08AF08	34.83	12713	65	300	0.82	14	1.33	4.33	1.00	1.33	2.00	4.33
W08AR01	34.05	17023	200	300	0.60	24	2.67	5.00	1.00	1.33	2.00	4.33
W08AR02	26	5197	50	150	0.75	24	2.67	3.33	1.33	1.67	2.00	5.00
W08AR03	32.13	3856	40	80	0.67	24	2.33	2.67	1.67	1.67	1.00	4.33
W08AR04	46.75	4442	47	48	0.51	24	2.67	1.67	1.67	1.67	1.00	4.33
W08AR07	60.2	12642	70	140	0.67	24	2.33	1.00	1.33	1.67	1.00	4.00
W08AR14	11.33	7023	320	300	0.48	24	2.33	3.33	1.00	1.67	2.00	4.67
W08AR24	448	447291	500	500	0.50	24	2.33	5.67	1.00	1.33	2.00	4.33
W08AR25	77.97	73294	470	470	0.50	24	3.00	5.67	1.00	1.67	2.00	4.67
W08AR26	91.05	59183	325	325	0.50	24	2.67	5.33	1.00	1.67	1.00	3.67
W08MC02	18.18	5000	75	200	0.73	16	2.33	4.33	1.00	2.00	2.00	5.00
W08MC03	12.79	3580	70	210	0.75	17	2.67	4.67	0.67	1.33	1.00	3.00
W08NA01	16.46	13165	400	400	0.50	18	2.33	4.00	3.00	2.00	4.00	9.00
W08NA02	2.1	1974	670	270	0.29	30	2.00	3.00	2.00	1.33	2.00	5.33
W08NA07	6.99	3844	275	275	0.50	24	3.00	4.00	0.67	1.67	1.00	3.33
W08NS01	23.27	10953	200	400	0.67	17	2.67	4.33	0.67	1.33	4.33	6.33
W08NS02	21.45	12867	200	400	0.67	12	3.00	4.33	1.33	1.67	2.67	5.67
W08NS03	1075	397618	185	185	0.50	12	2.67	4.33	0.67	1.33	1.67	3.67
W08NS04	188.9	94427	200	300	0.60	12	2.33	4.00	0.33	1.67	1.67	3.67
W08NS06	34.46	27398	300	495	0.62	12	3.00	4.67	1.00	1.67	2.00	4.67
W08NS07	61.04	54939	400	500	0.56	12	3.00	3.67	1.00	2.00	2.00	5.00
W08NS08	51.57	43053	390	445	0.53	24	3.00	6.00	1.33	1.67	3.00	6.00
W08NS09	155.1	116319	350	400	0.53	30	3.33	4.33	1.33	1.67	4.00	7.00
W08NS11	14.56	9098	200	425	0.68	20	3.00	3.33	1.33	1.67	2.00	5.00
W08NS12	16	15267	455	500	0.52	24	2.67	4.00	1.00	1.67	3.00	5.67
W08NS13	15.08	11011	245	485	0.66	15	2.33	3.67	1.00	1.33	1.00	3.33
W08NS16	14.24	5340	100	275	0.73	12	2.67	5.33	1.00	2.00	2.00	5.00

Table 18. DEA Output Data – Blue Shaded DMUs Selected for Funding

DMU	Score	Rank	Reference set (lambda)							
W08AF01	1	1	W08AF01	1						
W08AF05	1	1	W08AF05	1						
W08AR24	1	1	W08AR24	1						
W08AR25	1	1	W08AR25	1						
W08NA01	1	1	W08NA01	1						
W08NA02	1	1	W08NA02	1						
W08NS03	1	1	W08NS03	1						
W08NS07	1	1	W08NS07	1						
W08NS08	1	1	W08NS08	1						
W08NS09	1	1	W08NS09	1						
W08NS16	1	1	W08NS16	1						
W08NS06	0.9992	12	W08AF01	0.33549	W08AF05	0.13794	W08NS03	0.45856	W08NS16	6.72E-02
W08NA07	0.9928	13	W08AR25	8.24E-02	W08NS07	0.19509	W08NS09	0.65029		
W08NS02	0.9556	14	W08AF01	0.37097	W08AF05	0.31855	W08NS03	2.42E-02	W08NS07	0.24194
W08AR26	0.9412	15	W08AR24	0.23529	W08AR25	0.70588				
W08NS12	0.8766	16	W08NA01	7.63E-02	W08NS07	0.13542	W08NS08	0.23389	W08NS09	0.4142
W08AR04	0.8745	17	W08NS07	0.20084	W08NS09	0.61925				
W08NS04	0.8485	18	W08AF01	7.07E-02	W08AF05	3.08E-02	W08NS03	0.4811	W08NS16	0.26585
W08NS01	0.8223	19	W08AF05	0.18684	W08NA01	0.28394	W08NS03	0.45164	W08NS07	0.1005
W08AR14	0.7995	20	W08AR25	5.23E-02	W08NS07	8.87E-02	W08NS08	0.1087	W08NS09	0.47528
W08NS11	0.789	21	W08NS07	0.74801	W08NS09	0.22679				
W08AR01	0.7885	22	W08AR25	0.22536	W08NS03	0.25821	W08NS08	0.43401		
W08MC03	0.7387	23	W08NS03	0.91457	W08NS16	0.13191				
W08MC02	0.7361	24	W08AF05	0.28163	W08NS03	0.6898	W08NS08	4.99E-03		
W08AF08	0.7174	25	W08AF05	7.08E-02	W08NS03	8.32E-02	W08NS16	0.68297		
W08NS13	0.672	26	W08AF01	7.67E-02	W08AF05	2.71E-02	W08NS03	0.68611	W08NS07	5.01E-02
W08AF07	0.6593	27	W08AF01	0.24176	W08AF05	0.41758				
W08AR02	0.6335	28	W08NA01	3.72E-02	W08NS07	0.57895	W08NS09	0.25288		
W08AR03	0.6084	29	W08NS07	0.42664	W08NS09	0.31603				
W08AR07	0.6084	29	W08NS07	0.42664	W08NS09	0.31603				

Table 19. FY08 Facilities DEA Results

Red Column Headings Indicate Input Data

DMU	(O) ROI	$K Savings	Service	OSD	(I) % OSD	(I) Perform Period	(O) Accept Index	(O) Joint Index	Readiness Benefits Index	Logistics Benefits Index	Safety Benefits Index	(O) Total Benefits Index
F08AR01	7.08	6017	425	425	0.5	24	3.3333	8.33	1.33	2.00	3.00	6.33
F08AR02	13.47	13466	500	500	0.5	18	3	6.33	1.00	1.67	2.00	4.67
F08AR03	17.44	12211	350	350	0.5	18	2.3333	6.33	1.00	1.33	2.00	4.33
F08AR05	10.02	9019	450	450	0.5	24	1.6667	3.00	1.00	1.00	2.00	4.00
F08AR06	13.34	10669	400	400	0.5	18	2.6667	4.67	1.33	1.67	3.00	6.00
F08AR07	17.81	16915	475	475	0.5	24	3	5.67	1.33	1.67	3.00	6.00
F08AR09	8.29	7463	450	450	0.5	24	2.3333	4.67	1.00	1.67	5.00	7.67
F08AR11	14.37	5748	200	200	0.5	18	3	6.00	1.00	1.67	2.00	4.67
F08AR12	13.48	10787	400	400	0.5	18	2.6667	3.33	1.33	1.67	2.00	5.00
F08AR13	34.57	53589	775	775	0.5	24	2.6667	5.67	1.00	2.00	3.00	6.00
F08AR14	16.84	10106	300	300	0.5	18	2.6667	4.67	1.00	1.33	3.00	5.33
F08AR15	9.15	7774	425	425	0.5	24	2.3333	3.00	0.67	1.33	3.00	5.00
F08AR16	11.29	4515	200	200	0.5	18	2.6667	5.00	1.00	1.67	4.00	6.67
F08AR23	65.07	65073	500	500	0.5	18	3	5.33	1.33	2.00	5.00	8.33
F08AR24	84.56	80328	475	475	0.5	18	3.3333	7.00	1.33	1.67	3.00	6.00
F08NV01	127.5	1275000	500	500	0.5	12	3	6.67	1.00	1.33	3.00	5.33
F08NV17	5.18	6185	1114	80	0.067	24	3.3333	5.00	1.33	1.67	2.00	5.00
F08NV18	10	1000	0	100	1	21	2.6667	2.33	1.33	1.67	3.00	6.00
F08NV21	8.89	1111	60	65	0.52	24	2	2.67	1.00	1.33	3.00	5.33

Table 20. DEA Output Data – Blue Shaded DMUs Selected for Funding

DMU	Score	Rank	Reference set (lambda)					
F08AR23	1	1	F08AR23	1				
F08NV01	1	1	F08NV01	1				
F08NV17	1	1	F08NV17	1				
F08AR01	0.939767	4	F08NV01	0.872279	F08NV17	0.503627		
F08AR24	0.914034	5	F08AR23	4.08E-02	F08NV01	0.841856	F08NV17	0.233979
F08AR16	0.845029	6	F08AR23	0.642385	F08NV01	0.195367	F08NV17	5.43E-02
F08AR02	0.81541	7	F08NV01	0.786131	F08NV17	0.218492		
F08AR03	0.81541	7	F08NV01	0.786131	F08NV17	0.218492		
F08AR09	0.814508	9	F08AR23	0.784173	F08NV17	0.226379		
F08AR06	0.797534	10	F08AR23	0.44861	F08NV01	0.336395	F08NV17	9.35E-02
F08AR11	0.792507	11	F08NV01	0.76405	F08NV17	0.212355		
F08AR14	0.75426	12	F08AR23	0.240056	F08NV01	0.495741	F08NV17	0.137783
F08AR12	0.732624	13	F08AR23	0.13578	F08NV01	0.575413	F08NV17	0.159926
F08AR07	0.717237	14	F08AR23	0.284911	F08NV01	0.391049	F08NV17	0.308029
F08AR13	0.717237	14	F08AR23	0.284911	F08NV01	0.391049	F08NV17	0.308029
F08NV18	0.627866	16	F08AR23	0.419753	F08NV01	0.469136		
F08AR15	0.570517	17	F08AR23	0.349419	F08NV01	0.192675	F08NV17	0.212116
F08NV21	0.554605	18	F08AR23	0.558612	F08NV17	0.135646		
F08AR05	0.436996	19	F08AR23	0.359546	F08NV01	5.90E-02	F08NV17	0.137847

Table 21. FY09 Weapon System DEA Results

Red Column Headings Indicate Input Data

Index	OSD$	Service $	Total $	Savings $	(O) ROI	(I) Perform Period	(O) Accept Index	(O) Joint Index	Readiness Benefits Index	Logistics Benefits Index	Safety Benefits Index	(O) Combined Index	(I) %OSD Funds
W09AF01	$46	$48	$94	$4,680	49.79	12	2.80	6.00	1.60	1.60	1.40	4.60	0.49
W09AF02	$300	$125	$425	$116,919	275.10	12	2.20	3.80	1.40	1.40	1.00	3.80	0.71
W09AF04	$250	$100	$350	$12,097	34.57	12	1.67	5.00	1.33	1.33	1.33	4.00	0.71
W09AF05	$350	$150	$500	$14,364	35.91	12	1.67	3.00	0.33	1.00	1.33	2.67	0.70
W09AF06	$500	$125	$625	$89,793	276.29	12	2.40	5.80	1.20	1.60	2.00	4.80	0.80
W09AF07	$200	$100	$300	$24,132	80.44	12	2.20	4.20	1.20	1.40	1.40	4.00	0.67
W09AR01	$350	$350	$700	$447,291	638.99	24	2.20	5.40	1.40	1.25	1.40	4.05	0.50
W09AR02	$250	$1,103	$1,353	$542,280	400.80	9	2.80	5.40	1.20	1.60	3.60	6.40	0.18
W09AR03	$350	$75	$425	$50,990	119.98	12	2.40	5.60	1.80	1.60	3.40	6.80	0.82
W09AR04	$125	$100	$225	$7,023	31.22	18	1.80	1.75	1.50	1.50	1.00	4.00	0.56
W09AR07	$500	$300	$800	$15,929	19.91	12	2.50	4.25	1.75	2.00	3.75	7.50	0.63
W09NS01	$440	$260	$700	$9,627	13.75	24	2.40	4.40	1.80	1.80	2.80	6.40	0.63
W09NS02	$395	$395	$790	$142,072	179.84	24	2.40	4.20	1.40	1.60	2.00	5.00	0.50
W09NS04	$445	$390	$835	$75,724	90.70	24	3.00	4.40	1.40	1.60	3.00	6.00	0.53
W09NS06	$490	$390	$880	$18,238	20.49	28	2.60	4.00	1.40	1.40	2.20	5.00	0.56
W09NS07	$450	$450	$900	$20,576	22.86	24	2.20	4.40	1.40	1.40	2.20	5.00	0.50
W09NA01	$400	$400	$800	$9,427	11.78	12	2.80	5.00	1.40	1.40	2.20	5.00	0.50
W09NA02	$200	$200	$400	$4,439	11.10	19	2.75	4.50	1.25	1.25	2.00	4.50	0.50
W09NA03	$350	$1,500	$1,850	$11,718	6.33	19	2.60	6.00	1.20	1.40	3.00	5.60	0.19
W09MC02	$350	$175	$525	$85,504	162.86	12	2.60	5.40	1.60	1.60	2.20	5.40	0.67
W09MC03	$450	$250	$700	$31,022	44.32	24	2.80	5.80	1.80	1.80	2.80	6.40	0.64
W09MC04	$250	$65	$315	$3,464	11.00	12	2.00	6.00	1.80	1.80	2.20	5.80	0.79
W09MC06	$500	$300	$800	$151,795	189.74	24	2.75	4.50	1.25	1.50	2.00	4.75	0.63

Table 22. DEA Output Data – Blue Shaded DMUs Selected for Funding

No.	DMU	Score	Rank	Reference set (lambda)	
W09AF01	W09AR02	1	1	W09AR02	1
	W09NA03	1	1	W09NA03	1
	W09AR07	0.878906	3	W09AR02	1.171875
	W09AF01	0.833333	4	W09AR02	1.111111111
W09AF06	W09MC04	0.833333	4	W09AR02	1.111111111
	W09AF06	0.805556	6	W09AR02	1.074074074
W09AR01	W09AR03	0.796875	7	W09AR02	1.0625
W09AR02	W09NA01	0.75	8	W09AR02	1
W09AR03	W09MC02	0.75	8	W09AR02	1
W09AR04	W09AF04	0.694444	10	W09AR02	0.925925926
	W09AR01	0.597857	11	W09AR02	1.594286427
W09NS01	W09AF02	0.589286	12	W09AR02	0.785714286
	W09AF07	0.589286	12	W09AR02	0.785714286
W09NS04	W09NA02	0.465226	14	W09AR02	0.982142857
W09NS06	W09AF05	0.446429	15	W09AR02	0.595238095
W09NS07	W09MC03	0.402778	16	W09AR02	1.074074074
W09NA01	W09NS04	0.401786	17	W09AR02	1.071428571
W09NA02	W09NS01	0.375	18	W09AR02	1
W09NA03	W09MC06	0.368304	19	W09AR02	0.982142857
W09MC02	W09AR04	0.321429	20	W09AR02	0.642857143
	W09NS02	0.321429	20	W09AR02	0.857142857
W09MC04	W09NS06	0.308137	22	W09AR02	0.928571429
W09MC06	W09NS07	0.305556	23	W09AR02	0.814814815

Table 23. FY09 Facilities DEA Results

Red Column Headings Indicate Input Data

Index	OSD$	Service $	Total $	Savings $	(O) ROI	(I) Perform Period	(O) Accept Index	(O) Joint Index	Readiness Benefits Index	Logistics Benefits Index	Safety Benefits Index	(O) Combined Index	(I) %OSD Funds
F09AR01	$380	$380	$760	$6,863	9.03	24	3.17	6.33	1.17	1.50	3.83	6.50	0.50
F09AR02	$210	$210	$420	$12,981	30.91	18	3.17	6.67	1.00	1.50	3.50	6.00	0.50
F09AR03	$240	$240	$480	$4,991	10.40	24	2.67	6.33	0.83	1.50	1.83	4.17	0.50
F09AR04	$275	$275	$550	$12,706	23.10	18	2.67	6.00	1.17	1.33	1.17	3.67	0.50
F09AR07	$395	$395	$790	$15,000	18.99	24	3.20	5.60	1.20	1.60	4.20	7.00	0.50
F09AR08	$350	$350	$700	$12,038	17.20	24	2.83	5.83	1.33	1.50	1.83	4.67	0.37
F09AR10	$310	$310	$620	$7,789	12.56	24	2.50	6.67	1.17	1.67	2.33	5.17	0.50
F09AR11	$185	$185	$370	$3,669	9.92	18	2.80	6.20	0.60	1.40	1.20	3.20	0.50
F09AR12	$215	$215	$430	$8,492	19.75	24	3.00	6.00	1.00	0.75	3.50	5.25	0.50
F09AR13	$345	$345	$690	$17,448	25.29	18	3.00	6.40	0.80	1.60	3.60	6.00	0.50
F09AR14	$235	$235	$470	$9,655	20.54	18	3.00	5.17	1.50	1.50	2.33	5.33	0.50
F09AR16	$425	$425	$850	$8,433	9.92	22	2.67	5.50	1.33	1.50	2.67	5.50	0.50
F09AR17	$175	$175	$350	$4,314	12.33	24	2.67	5.50	1.17	1.67	1.33	4.17	0.50
F09AR18	$235	$235	$470	$10,525	22.39	18	2.17	6.33	0.83	1.33	3.17	5.33	0.50
F09NV01	$500	$500	$1,000	$0	0	12	2.40	5.00	0.80	0.75	1.00	2.55	0.50
F09NV04	$90	$90	$180	$448	2.49	24	3.00	6.33	1.00	1.50	1.83	4.33	0.50
F09NV05	$80	$80	$160	$537	3.36	20	3.00	6.83	1.33	1.83	3.33	6.50	0.50
F09NV07	$400	$0	$400	$1,165	2.91	24	2.60	4.80	1.40	1.80	2.40	5.60	1.00
F09NV08	$150	$0	$150	$1,979	13.19	24	3.50	4.40	1.20	1.60	2.40	5.20	1.00
F09NV09	$680	$313	$993	$18,281	18.41	24	2.25	5.25	1.50	1.25	4.00	6.75	0.68

Table 24. DEA Output Data – Blue Shaded DMUs Selected for Funding

DMU	Score	Rank	Reference set (lambda)							
F09AR02	1	1	F09AR02	1						
F09AR07	1	1	F09AR07	1						
F09AR08	1	1	F09AR08	1						
F09AR13	1	1	F09AR02	1						
F09NV01	1	1	F09NV01	1						
F09NV05	1	1	F09NV05	1						
F09AR01	0.975974	7	F09AR02	2.64E-02	F09AR07	0.420866	F09AR08	0.248893	F09NV05	0.343688
F09AR18	0.95	8	F09AR02	0.95						
F09AR14	0.947368	9	F09AR02	0.947368						
F09AR10	0.930666	10	F09AR02	0.11202	F09AR08	0.432114	F09NV05	0.497444		
F09AR11	0.93	11	F09AR02	0.93						
F09AR04	0.9	12	F09AR02	0.9						
F09NV04	0.884193	13	F09AR02	0.380819	F09AR08	0.470622	F09NV05	0.153548		
F09AR03	0.884122	14	F09AR02	5.65E-02	F09AR08	0.399568	F09NV05	0.530635		
F09AR12	0.872715	15	F09AR02	0.506215	F09AR08	0.493054				
F09NV09	0.84375	16	F09AR02	1.125						
F09AR16	0.841682	17	F09AR02	0.155461	F09AR07	0.249569	F09AR08	0.109051	F09NV05	0.355592
F09NV08	0.779908	18	F09AR02	0.562055	F09NV01	0.716733				
F09AR17	0.775747	19	F09AR02	0.449969	F09AR08	0.43827				
F09NV07	0.7	20	F09AR02	0.933333						

Table 25. FY10 Weapon System DEA Results

Red Column Headings Indicate Input Data – Cost of Corrosion replaced Acceptance Index

Index	OSD$	Service $	Total $	Savings $	(O) ROI	(I) Perform Period	(O) Cost of Corrosion	(O) Joint Index	Readiness Benefits Index	Logistics Benefits Index	Safety Benefits Index	(O) Combined Benefits	(I) %OSD Funds
W10AF01	320	$330	$650	$39,727	$61	11.00	18.16	5.00	1.25	1.75	3.00	6.00	0.49
W10AF03	500	$250	$750	$5,509	$7	8.00	18.16	6.50	1.00	1.25	3.00	5.25	0.67
W10AF05	500	$386	$886	$78,924	$89	11.00	7.1	6.00	1.33	1.33	3.00	5.67	0.56
W10AF06	245	$763	$1,008	$0	$0	11.00	1.88	4.00	1.25	1.25	3.00	5.50	0.24
W10AF07	300	$260	$560	$339,002	$605	8.00	18.16	6.00	1.33	1.25	3.00	5.58	0.54
W10AR01	220	$300	$520	$25,090	$48	24.00	6.2	7.25	1.00	1.50	3.00	5.50	0.42
W10AR03	335	$165	$500	$17,023	$34	6.00	61.2	5.00	1.50	1.50	4.00	7.00	0.67
W10AR04	290	$720	$1,010	$29,639	$29	24.00	1.65	3.75	1.00	1.50	3.00	5.50	0.29
W10AR05	325	$150	$475	$3,240	$7	22.00	6.2	4.50	1.50	1.50	3.00	6.00	0.68
W10AR09	30	$0	$30	$223	$7	24.00	10.97	4.25	1.75	1.75	3.00	6.50	1.00
W10NS01	500	$800	$1,300	$23,385	$18	21.00	1.14	3.33	1.33	1.33	3.00	5.67	0.38
W10NS02	380	$400	$780	$69,258	$89	24.00	9.62	3.50	1.33	1.33	4.00	6.67	0.49
W10NS03	390	$320	$710	$17,539	$25	24.00	9.62	4.00	1.00	1.50	3.00	5.50	0.55
W10NS04	350	$350	$700	$29,078	$42	18.00	9.62	3.67	1.00	1.67	3.00	5.67	0.50
W10NS06	490	$0	$490	$105,514	$215	22.00	9.62	2.67	1.00	1.33	3.00	5.33	1.00
W10NS07	500	$600	$1,100	$30,049	$27	24.00	4.86	3.50	1.00	1.75	3.00	5.75	0.45
W10NS08	480	$300	$780	$33,264	$43	24.00	8.56	4.00	1.25	1.75	3.00	6.00	0.62
W10NA01	200	$200	$400	$7,405	$19	15.00	21.66	3.67	1.33	1.33	3.00	5.67	0.50
W10NA02	500	$200	$700	$2,043	$3	23.00	4.71	3.25	1.75	1.75	4.00	7.50	0.71
W10NA03	334	$256	$590	$6,270	$11	13.00	21.66	3.75	1.00	1.50	3.00	5.50	0.57
W10NA05	250	$450	$700	$3,339	$5	21.00	21.66	4.75	1.33	1.25	3.00	5.58	0.36
W10NA06	350	$0	$350	$3,762	$11	12.00	2.42	5.50	1.50	1.50	3.00	6.00	1.00
W10NA07	100	$100	$200	$7,213	$36	21.00	21.66	4.25	1.25	1.25	3.00	5.50	0.50
W10NA08	500	$189	$689	$11,276	$16	24.00	2.74	2.67	1.67	1.67	3.00	6.33	0.73
W10MC01	400	$200	$600	$2,745	$5	24.00	6.5	5.00	2.00	2.00	4.50	8.50	0.67
W10MC02	400	$300	$700	$31,022	$44	24.00	8.92	6.00	2.00	2.00	4.50	8.50	0.57
W10MC03	200	$200	$400	$1,168	$3	21.00	6.23	5.75	1.50	1.75	4.50	7.75	0.50
W10MC04	300	$250	$550	$82,523	$150	24.00	14.26	5.75	1.25	1.50	3.00	5.75	0.55
W10MC05	200	$350	$550	$34,639	$63	23.00	8.92	5.50	1.25	1.50	3.00	5.75	0.36
W10MC06	300	$300	$600	$26,642	$44	24.00	0	4.25	1.75	1.75	3.00	6.50	0.50
W10MC07	200	$220	$420	$15,070	$36	18.00	8.92	4.75	1.25	1.25	3.00	5.50	0.48
W10MC08	175	$175	$350	$12,758	$36	24.00	8.87	5.25	1.75	1.50	4.00	7.25	0.50
W10MC09	250	$300	$550	$151,795	$276	24.00	8.92	5.00	1.75	1.75	4.00	7.50	0.45
W10MC10	175	$140	$315	$6,347	$20	12.00	0	5.00	1.50	1.75	4.50	7.75	0.56

Table 26. DEA Output Data – Blue Shaded DMUs Selected for Funding

DMU	Score	Rank	Reference set (lambda)									
W10AF03	1	1	W10AF03	1								
W10AF06	1	1	W10AF06	1								
W10AF07	1	1	W10AF07	1								
W10AR01	1	1	W10AR01	1								
W10AR03	1	1	W10AR03	1								
W10NA05	1	1	W10NA05	1								
W10MC09	1	1	W10MC09	1								
W10MC05	0.9819	8	W10AF06	0.43079	W10AF07	7.74E-02	W10AR01	0.312748	W10NA05	0.220034		
W10MC10	0.9502	9	W10AF06	0.75485	W10AF07	4.58E-03	W10AR03	0.510392				
W10AR04	0.8921	10	W10AF06	0.85501	W10MC09	0.10633						
W10AF05	0.8867	11	W10AF06	0.30951	W10AF07	0.79366						
W10AF01	0.8674	12	W10AF06	0.52886	W10AF07	0.32817	W10AR03	0.183107				
W10MC04	0.7499	13	W10AF06	0.16528	W10AF07	0.22339	W10AR01	0.269135	W10AR03	7.32E-04	W10NA05	0.377614
W10NS02	0.7464	14	W10AF06	0.58641	W10AF07	3.84E-02	W10NA05	0.265126	W10MC09	0.232885		
W10NA01	0.7438	15	W10AF06	0.47576	W10AF07	1.42E-02	W10AR03	0.263864	W10NA05	0.201294		
W10MC02	0.7426	16	W10AF06	1.28872	W10AF07	0.07004	W10AR03	0.037142	W10NA05	0.136291		
W10MC03	0.7399	17	W10AF06	1.29731	W10AR01	3.60E-02	W10AR03	5.73E-02	W10NA05	2.87E-03		
W10MC08	0.7349	18	W10AF06	0.9262	W10AF07	3.27E-02	W10NA05	0.278836	W10MC09	5.55E-02		
W10NA07	0.7345	19	W10AF06	0.20413	W10AF07	4.77E-02	W10AR03	0.131066	W10NA05	0.571968		
W10MC07	0.6914	20	W10AF06	0.77659	W10AF07	4.40E-02	W10AR01	0.1239	W10AR03	9.63E-02		
W10NS01	0.672	21	W10AF06	0.94142	W10MC09	6.52E-02						
W10MC01	0.6531	22	W10AF06	1.33455	W10AR03	0.16571						
W10NA03	0.6435	23	W10AF06	0.56924	W10AR03	0.33482	W10NA05	4.55E-03				
W10NS04	0.6174	24	W10AF06	0.78063	W10AF07	6.30E-02	W10AR03	0.089467	W10NA05	7.07E-02		
W10MC06	0.6141	25	W10AF06	0.96243	W10MC09	0.16089						
W10NS07	0.6133	26	W10AF06	0.79612	W10NA05	0.11534	W10MC09	9.70E-02				
W10NA06	0.5855	27	W10AF03	6.40E-02	W10AF07	0.51605	W10AR03	0.397519				
W10NA02	0.5754	28	W10AF06	1.08281	W10AR03	0.22065						
W10NS03	0.5369	29	W10AF06	0.66867	W10AF07	3.66E-02	W10AR03	4.18E-02	W10NA05	0.237445		
W10NS08	0.5144	30	W10AF06	0.84527	W10AF07	6.64E-02	W10AR03	5.76E-02	W10NA05	0.103324		
W10AR05	0.4876	31	W10AF06	0.84953	W10AF07	7.63E-02	W10AR03	0.128757				
W10NA08	0.4722	32	W10AF06	0.93004	W10AF07	0.01806	W10AR03	0.159609				
W10AR09	0.4195	33	W10AF06	0.71523	W10AR03	0.3666						
W10NS06	0.3853	34	W10AF06	0.44332	W10AF07	0.34807	W10AR03	0.13596				

Table 27. FY10 Facilities DEA Results

Red Column Headings Indicate Input Data

Index	OSD$	Service $	Total $	Savings $	(O) ROI	(I) Perform Period	(O) Cost of Corrosion	(O) Joint Index	Readiness Benefits Index	Logistics Benefits Index	Safety Benefits Index	(O) Combined Benefits Index	(I) %OSD Funds
F10AR01	$350	$350	$700	$15,735	22.48	24	24.55	6.00	1.00	1.50	3.00	5.50	0.50
F10AR02	$180	$180	$360	$6,147	17.08	15	10.04	5.75	1.00	1.00	3.00	5.00	0.50
F10AR04	$275	$275	$550	$5,930	10.78	18	18.72	5.25	1.00	1.33	5.25	7.58	0.50
F10AR06	$475	$475	$950	$46,153	48.58	15	0.00	5.00	6.50	1.33	3.00	10.83	0.50
F10AR07	$325	$325	$650	$13,187	20.29	24	8.62	4.50	1.33	1.25	3.00	5.58	0.50
F10AR08	$275	$275	$550	$4,759	8.65	24	6.73	4.00	1.00	1.25	3.00	5.25	0.50
F10AR10	$300	$300	$600	$13,492	22.49	22	10.04	5.00	1.00	1.25	3.00	5.25	0.50
F10AR12	$200	$200	$400	$5,694	14.24	18	10.04	4.50	1.00	1.00	3.00	5.00	0.50
F10AR15	$665	$665	$1,330	$23,212	17.45	22	6.73	5.25	1.00	1.00	3.00	5.00	0.50
F10AR18	$230	$230	$460	$9,523	20.70	18	8.22	5.00	1.00	1.25	3.00	5.25	0.50
F10AR19	$370	$370	$740	$9,748	13.17	18	0.00	4.25	1.33	1.25	4.00	6.58	0.50
F10NV01	$340	$290	$630	$725	1.15	22	10.04	4.25	1.00	1.25	3.00	5.25	0.54
F10NV02	$175	$217	$392	$1,832	4.67	24	2.07	4.50	1.25	1.25	3.00	5.50	0.45
F10NV03	$100	$100	$200	$47	0.24	22	2.85	5.00	1.33	1.33	3.00	5.67	0.50
F10NV04	$75	$75	$150	$55,000	366.67	22	18.72	5.75	1.00	1.50	3.00	5.50	0.50
F10NV05	$180	$80	$260	$368	1.42	22	2.85	4.00	1.50	1.50	3.00	6.00	0.69
F10NV06	$190	$200	$390	$289	0.74	18	4.53	5.00	1.25	1.50	3.00	5.75	0.49
F10NV07	$250	$250	$500	$12,519	25.04	20	0.00	4.25	1.25	1.75	3.00	6.00	0.50
F10NV10	$160	$5,750	$5,910	0	0	22	10.04	4.00	1.00	1.67	3.00	5.67	0.03

Table 28. DEA Output Data – Blue Shaded DMUs Selected for Funding

DMU	Score	Rank	Reference set (lambda)									
F10AR01	1	1	F10AR01	1								
F10AR02	1	1	F10AR02	1								
F10AR04	1	1	F10AR04	1								
F10AR06	1	1	F10AR06	1								
F10NV04	1	1	F10NV04	1								
F10NV10	1	1	F10NV10	1								
F10NV06	0.8283	7	F10AR02	0.6283	F10AR06	0.17155	F10NV10	0.13232				
F10AR18	0.8113	8	F10AR02	0.6937	F10AR06	0.10072	F10NV04	1.08E-02	F10NV10	0.1113		
F10AR12	0.7603	9	F10AR02	0.4849	F10AR04	0.23218	F10AR06	3.45E-02	F10NV04	4.85E-03	F10NV10	7.32E-02
F10AR15	0.7558	10	F10AR02	0.7288	F10NV04	1.37E-02	F10NV10	0.24518				
F10AR10	0.7354	11	F10AR02	0.5983	F10AR04	6.76E-02	F10AR06	2.98E-02	F10NV04	2.75E-02	F10NV10	0.224309
F10NV03	0.7306	12	F10AR02	0.5956	F10AR06	0.1219	F10NV10	0.24138				
F10AR19	0.7267	13	F10AR02	0.3106	F10AR06	0.41053	F10NV10	0.10289				
F10NV07	0.6783	14	F10AR02	0.3564	F10AR06	0.3017	F10NV04	1.17E-02	F10NV10	0.15619		
F10NV02	0.659	15	F10AR02	0.4371	F10AR06	0.13337	F10NV10	0.3299				
F10AR07	0.6444	16	F10AR02	0.3906	F10AR04	9.70E-02	F10AR06	0.1253	F10NV04	1.77E-02	F10NV10	0.254131
F10NV01	0.6358	17	F10AR02	0.331	F10AR04	0.28711	F10AR06	6.09E-02	F10NV10	0.13369		
F10AR08	0.5714	18	F10AR02	0.3366	F10AR04	5.28E-02	F10AR06	0.16924	F10NV10	0.23524		
F10NV05	0.524	19	F10AR02	0.3453	F10AR06	0.37856	F10NV10	3.04E-02				

Table 29. FY11 Weapon System DEA Results

Red Column Headings Indicate Input Data

Index	OSD$	Service $	Total $	Savings $	(O) ROI	(I) Perform Period	(O) Cost of Corrosion	Readiness Benefits Index	Logistics Benefits Index	Safety Benefits Index	(O) Joint Index	(O) Combined Benefits Index	(I) %OSD Funds
W11AF01	$ 325	$ 100	$ 425	$ 79,453	187.0	12	11.18	0.60	0.40	0.60	3.80	1.60	0.76
W11AF02	$ 550	$ 200	$ 750	$ 31,464	42	24	12.22	1.20	0.80	0.60	4.20	2.60	0.73
W11AF04	$ 335	$ 100	$ 435	$ 5,274	12.1	12	14.83	0.60	0.80	0.60	3.80	2.00	0.77
W11AF06	$ 70	$ 70	$ 140	$ 4,761	34	18	11.83	1.00	1.00	1.20	4.40	3.20	0.50
W11AF07	$ 200	$ 100	$ 300	$ 23,880	79.6	6	13.83	0.80	1.00	1.20	4.00	3.00	0.67
W11AF08	$ 500	$ 250	$ 750	$ 2,482	4	12	3.17	0.80	0.60	0.60	3.80	2.00	0.67
W11AF09	$ 500	$ 407	$ 907	$ 72,673	80.1	12	7.24	0.60	1.20	1.20	3.80	3.00	0.55
W11AR01	$ 325	$ 100	$ 425	$ 218,580	364.3	15	11.86	1.00	0.83	1.00	3.00	2.83	0.76
W11AR02	$ 195	$ 195	$ 390	$ 12,330	31.6	24	1.40	1.20	1.00	1.20	4.40	3.40	0.50
W11AR03	$ 220	$ 1,280	$1,500	$ 182,645	121.8	24	11.58	0.83	1.33	1.00	2.83	3.17	0.15
W11AR04	$ 250	$ 560	$ 810	$ 4,706	5.8	24	13.00	0.80	1.60	3.60	5.60	6.00	0.31
W11AR05	$ 490	$ 490	$ 980	$ 97,253	99.2	24	26.90	1.40	2.00	1.80	6.20	5.20	0.50
W11AR09	$ 250	$ 250	$ 500	$ 99,547	199.1	24	17.45	0.83	0.67	1.00	3.17	2.50	0.50
W11AR10	$ 176	$ 176	$ 352	$ 18,506	52.6	12	37.02	1.00	0.83	1.00	4.00	2.83	0.50
W11AR12	$ 350	$ 125	$ 475	$ 6,872	14.5	24	20.80	1.80	1.60	1.20	6.80	4.60	0.74
W11MC01	$ 150	$ 150	$ 300	$ 24,569	81.9	12	31.67	1.40	1.20	1.20	4.00	3.80	0.50
W11MC02	$ 160	$ 140	$ 300	$ 965	3.2	24	14.81	1.80	2.00	1.20	4.60	5.00	0.53
W11MC03	$ 160	$ 140	$ 300	$ 339	1.1	24	14.81	2.00	2.20	1.20	4.60	5.40	0.53
W11MC04	$ 110	$ 110	$ 220	$ 1,836	8.4	24	13.76	1.20	1.00	0.60	4.60	2.80	0.50
W11MC05	$ 150	$ 150	$ 300	$1,035,452	3451	24	28.94	1.00	0.80	1.80	5.20	3.60	0.50
W11MC06	$ 200	$ 200	$ 400	$ 9,629	24.1	12	43.11	1.25	1.75	0.75	6.50	3.75	0.50
W11MC07	$ 275	$ 150	$ 425	$ 5,737	13.5	24	22.86	1.20	1.00	1.20	3.60	3.40	0.65
W11MC08	$ 100	$ 100	$ 200	$ 31,022	44.3	24	24.00	1.40	1.00	1.20	4.60	3.60	0.50
W11MC09	$ 200	$ 200	$ 400	$ 26,058	65.1	12	16.04	1.40	1.80	0.60	4.40	3.80	0.50
W11NA01	$ 250	$ 250	$ 500	$ 702	1.4	24	9.53	0.80	1.00	1.20	3.80	3.00	0.50
W11NA02	$ 60	$ 30	$ 90	$ 338	3.8	10	20.94	1.25	1.75	0.75	2.75	3.75	0.67
W11NA03	$ 200	$ 200	$ 400	$ 2,133	5.3	11	5.76	1.00	1.25	1.50	6.00	3.75	0.50
W11NA04	$ 285	$ 100	$ 385	$ 13,358	34.7	12	17.00	0.83	1.00	1.00	3.17	2.83	0.74
W11NA05	$ 460	$ 50	$ 510	$ 24,455	48	24	13.00	1.40	1.00	0.60	3.40	3.00	0.90
W11NS01	$ 500	$ 400	$ 900	$ 30,453	33.9	24	4.12	1.00	1.17	1.50	2.67	3.67	0.56
W11NS02	$ 480	$ 800	$1,280	$ 332,120	259.5	24	9.18	0.83	1.00	1.00	3.00	2.83	0.38
W11NS04	$ 400	$ 700	$1,100	$ 27,808	25.3	24	6.58	1.17	1.17	1.00	2.83	3.33	0.36
W11NS05	$ 450	$ 450	$ 900	$ 290,607	322.9	24	6.94	0.83	0.83	1.50	3.17	3.17	0.50
W11NS06	$ 500	$ 500	$1,000	$ 34,451	34.5	12	8.24	1.20	1.20	0.60	3.40	3.00	0.50

Table 30. DEA Output Data – Blue Shaded DMUs Selected for Funding

DMU	Score	Rank	Reference set (lambda)									
W11AF07	1	1	W11AF07	1								
W11AR03	1	1	W11AR03	1								
W11AR04	1	1	W11AR04	1								
W11MC01	1	1	W11MC01	1								
W11MC05	1	1	W11MC05	1								
W11MC06	1	1	W11MC06	1								
W11NA03	1	1	W11NA03	1								
W11MC09	0.980998	8	W11AR04	2.81E-02	W11MC01	0.382815	W11MC05	8.85E-03	W11NA03	0.572002		
W11NA02	0.971741	9	W11AF07	0.554352	W11MC06	0.269597	W11NA03	0.286921				
W11AR10	0.871249	10	W11MC05	9.29E-03	W11MC06	0.852675						
W11AR05	0.821122	11	W11AR04	0.576398	W11MC01	7.00E-03	W11MC05	2.46E-02	W11MC06	0.427867	W11NA03	5.84E-03
W11MC03	0.818636	12	W11AR04	0.576757	W11MC06	0.116031	W11NA03	0.401159				
W11NS06	0.766561	13	W11AR04	0.032498	W11MC01	0.130452	W11MC05	5.91E-03	W11NA03	0.610139		
W11MC02	0.758949	14	W11AR04	0.533	W11MC06	0.136908	W11NA03	0.343625				
W11AF09	0.748719	15	W11AF07	4.80E-02	W11MC01	6.72E-02	W11MC05	1.95E-02	W11NA03	0.674771		
W11AR12	0.667762	16	W11AR04	0.254176	W11MC06	0.827171						
W11MC08	0.634112	17	W11AR03	0.18529	W11AR04	0.227825	W11MC05	2.87E-03	W11MC06	0.43626		
W11NA04	0.633804	18	W11AF07	0.34279	W11MC01	1.34E-03	W11MC06	0.253205	W11NA03	0.22676		
W11AF06	0.629357	19	W11AR04	0.228183	W11MC05	6.59E-03	W11MC06	0.392846	W11NA03	8.91E-02		
W11MC04	0.601448	20	W11AR04	0.434975	W11MC06	0.332944						
W11AR01	0.593619	21	W11AF07	0.280995	W11MC01	0.103263	W11MC05	9.61E-02	W11NA03	0.333846		
W11AF01	0.586616	22	W11AF07	0.423544	W11MC05	4.24E-02	W11MC06	0.290059				
W11AR02	0.5773	23	W11AR04	0.412988	W11MC05	6.26E-03	W11MC06	0.316114				
W11AF08	0.558824	24	W11AF07	0.223529	W11MC06	0.447059						
W11NS01	0.551973	25	W11AR04	0.371236	W11MC05	8.62E-03	W11NA03	0.375523				
W11NS04	0.544742	26	W11AR04	0.501638	W11MC05	6.37E-03	W11NA03	8.02E-02				
W11AF04	0.543929	27	W11AF07	0.352616	W11MC06	0.367621						
W11NS05	0.526271	28	W11AR04	0.327541	W11MC05	9.27E-02	W11NA03	0.231425				
W11NS02	0.504176	29	W11AR04	0.402172	W11MC05	7.41E-02	W11MC06	5.57E-02				
W11MC07	0.50343	30	W11AR04	0.259442	W11MC01	1.58E-02	W11MC06	0.435062	W11NA03	0.040465		
W11NA01	0.496848	31	W11AR04	0.359328	W11MC06	0.275041						
W11AR09	0.465497	32	W11AR03	0.138604	W11AR04	0.129035	W11MC05	5.05E-02	W11MC06	0.294661		
W11AF02	0.415989	33	W11AR04	0.154396	W11MC05	8.37E-03	W11MC06	0.506436				
W11NA05	0.400792	34	W11AR04	7.44E-02	W11MC01	0.308858	W11MC05	5.90E-03	W11NA03	0.362313		

Table 31. FY11 Facilities DEA Results

Red Column Headings Indicate Input Data

Index	OSD$	Service $	Total $	Savings $	(O) ROI	(I) Perform Period	(O) Cost of Corrosion	Readiness Benefits Index	Logistics Benefits Index	Safety Benefits Index	(O) Joint Index	(O) Combined Benefits	(I) %OSD Funds
F11AF09	$ 74	$ 48	$ 122	$ 302	2.50	18	3.71	1.50	1.75	0.75	9.00	4.00	0.61
F11AR01	$ 300	$ 300	$ 600	$ 6,254	10.40	24	2.88	2.00	1.50	0.75	8.00	4.25	0.50
F11AR02	$ 230	$ 230	$ 460	$ 4,752	10.30	24	5.18	0.75	1.50	0.75	7.00	3.00	0.50
F11AR03	$ 180	$ 180	$ 360	$ 5,119	14.20	24	7.27	0.75	1.50	0.75	7.00	3.00	0.50
F11AR04	$ 500	$ 500	$ 1,000	$ 26,431	26.40	24	20.57	2.00	2.00	0.75	7.75	4.75	0.50
F11AR08	$ 250	$ 250	$ 500	$ 7,445	14.90	24	13.25	1.50	1.50	0.75	8.50	3.75	0.50
F11AR15	$ 400	$ 400	$ 800	$ 13,497	16.90	24	10.03	1.75	1.00	2.25	8.25	5.00	0.50
F11AR16	$ 300	$ 300	$ 600	$ 25,061	41.80	24	9.34	1.00	2.00	2.00	11.33	5.00	0.50
F11AR17	$ 475	$ 525	$ 1,000	$ 21,890	21.9	24	3.00	1.75	1.50	2.25	10.25	5.50	0.48
F11AR18	$ 400	$ 400	$ 800	$ 7,445	14.9	24	3.25	1.25	1.50	0.75	7.25	3.50	0.50
F11AR19	$ 375	$ 375	$ 750	$ 9,746	13.00	24	3.50	1.00	1.00	3.00	6.25	5.00	0.50
F11AR22	$ 200	$ 200	$ 400	$ 4,411	11	24	7.07	1.00	1.25	0.75	7.25	3.00	0.50
F11AR23	$ 375	$ 375	$ 750	$ 7,789	10.4	24	4.96	1.25	1.50	0.75	7.25	3.50	0.50
F11AR24	$ 275	$ 275	$ 550	$ 5,956	10.8	24	5.04	1.25	1.25	1.50	7.00	4.00	0.50
F11AR25	$ 225	$ 225	$ 450	$ 4,719	10.5	24	4.21	2.25	1.75	0.00	4.75	4.00	0.50
F11AR26	$ 250	$ 250	$ 500	$ 5,668	11.3	24	3.68	1.50	1.25	0.75	7.50	3.50	0.50
F11AR27	$ 450	$ 450	$ 900	$ 12,255	13.6	24	5.93	1.75	1.50	2.25	7.00	5.50	0.50
F11NV02	$ 185	$ 90	$ 275	$ 368	1.34	24	2.96	2.25	1.75	2.25	7.75	6.25	0.67
F11NV04	$ 100	$ 150	$ 250	$ -	0	24	2.45	2.00	1.33	2.00	9.00	5.33	0.40
F11NV05	$ 260	$ 260	$ 520	$ 14,460	27.8	24	2.50	2.00	1.75	0.75	6.25	4.50	0.50
F11NV06	$ 150	$ 150	$ 300	$ 1,378	4.6	24	5.25	1.25	2.00	0.75	8.25	4.00	0.50
F11NV07	$ 200	$ 300	$ 500	$ 1,603	3.2	24	4.93	2.25	2.25	3.00	8.50	7.50	0.40
F11NV08	$ 125	$ 125	$ 250	$ 969	3.9	12	1.92	1.00	1.50	0.75	6.25	3.25	0.50
F11NV09	$ 100	$ 100	$ 200	$ 1,783	8.9	12	6.23	1.33	2.33	1.00	5.67	4.67	0.50

Table 32. DEA Output Data – Blue Shaded DMUs Selected for Funding

DMU	Score	Rank	Reference set (lambda)							
F11AR04	1	1	F11AR04	1						
F11AR16	1	1	F11AR16	1						
F11NV04	1	1	F11NV04	1						
F11NV07	1	1	F11NV07	1						
F11NV08	1	1	F11NV08	1						
F11NV09	1	1	F11NV09	1						
F11AF09	0.995542	7	F11AR16	0.285606	F11NV08	0.9221				
F11AR17	0.968735	8	F11AR16	0.708421	F11NV07	0.257293	F11NV09	6.04E-03		
F11AR08	0.889241	9	F11AR04	0.440391	F11AR16	0.44885				
F11AR15	0.86275	10	F11AR04	0.25049	F11AR16	0.345334	F11NV07	0.222438	F11NV09	8.90E-02
F11NV05	0.807581	11	F11AR16	0.642874	F11NV07	0.137256	F11NV09	5.49E-02		
F11AR27	0.798006	12	F11AR04	1.57E-02	F11AR16	0.242753	F11NV07	0.449669	F11NV09	0.179867
F11NV02	0.774349	13	F11AR16	0.072324	F11NV07	0.362102	F11NV09	0.679846		
F11NV06	0.747452	14	F11AR16	0.653801	F11NV07	0.078042	F11NV09	0.031217		
F11AR01	0.744903	15	F11AR16	0.557602	F11NV07	0.156084	F11NV09	6.24E-02		
F11AR19	0.728955	16	F11AR16	0.245905	F11NV07	0.402542	F11NV09	0.161017		
F11AR26	0.672117	17	F11AR16	0.622425	F11NV07	4.14E-02	F11NV09	1.66E-02		
F11AR24	0.667021	18	F11AR16	0.430028	F11NV07	0.197494	F11NV09	0.078998		
F11AR22	0.664012	19	F11AR04	7.69E-02	F11AR16	0.587136				
F11AR18	0.656031	20	F11AR16	0.57767	F11NV07	6.53E-02	F11NV09	2.61E-02		
F11AR23	0.656031	20	F11AR16	0.57767	F11NV07	6.53E-02	F11NV09	2.61E-02		
F11AR03	0.651062	22	F11AR04	0.105685	F11AR16	0.545377				
F11AR02	0.617647	23	F11AR16	0.617647						
F11AR25	0.584105	24	F11AR16	0.199342	F11NV07	0.320636	F11NV09	0.128254		

Table 33. FY12 Combined Weapon System and Facilities DEA Results*

Red Column Headings Indicate Input Data

Index	OSD$	Service $	Total $	Savings $	(O) ROI	(I) Perform Period	(O) Cost of Corrosion	Readiness Benefits Index	Logistics Benefits Index	Safety Benefits Index	(O) Joint Index	(O) Combined Benefits Index	(I) %OSD Funds
W12AF02	100	50	150	4284	28.6	24	18	0.62	1.23	1.69	4.38	3.54	0.67
W12AF03	150	150	300	2163	7.2	18	18	1.00	1.00	1.08	3.31	3.08	0.50
W12AR01	400	400	800	5025	6.3	21	0	1.08	1.15	1.38	2.69	3.62	0.50
W12AR02	492	334	826	3129	3.8	24	12	0.38	0.38	0.15	1.92	0.92	0.60
W12AR04	500	175	675	125368	185.7	24	23	0.92	0.92	0.92	3.08	2.77	0.74
W12AR05	200	200	400	25417	63.5	24	2	0.62	1.08	0.92	2.85	2.62	0.50
W12AR06	400	200	600	7309	12.2	24	12	1.00	1.00	1.15	2.54	3.15	0.67
W12AR07	200	200	400	28290	70.7	24	17	0.38	0.77	0.54	1.92	1.69	0.50
W12AR09	450	450	900	213849	237.6	12	0	0.46	1.08	1.00	1.46	2.54	0.50
W12AR10	300	200	500	93582	187.2	8	1	0.85	1.00	1.00	2.38	2.85	0.60
W12AR11	500	560	1060	18422	17.4	8	61	1.15	1.23	1.38	3.54	3.77	0.47
W12AR12	135	165	300	29067	96.9	24	61	0.85	1.15	1.00	3.62	3.00	0.45
W12MC01	300	250	550	16217	29.5	24	30	0.62	0.85	0.77	2.00	2.23	0.55
W12MC03	275	275	550	14814	26.9	8	22	0.77	1.23	1.00	2.69	3.00	0.50
W12MC04	150	150	300	18592	62.0	12	36	0.77	0.85	0.62	2.00	2.23	0.50
W12MC05	200	200	400	7272	18.2	21	15	0.77	0.92	0.62	2.77	2.31	0.50
W12MC06	300	250	550	10131	18.4	24	30	0.54	1.00	1.00	3.08	2.54	0.55
W12MC07	150	150	300	2301	7.7	12	22	0.54	0.77	0.54	2.23	1.85	0.50
W12MC08	300	300	600	50834	84.7	18	17	0.31	0.69	0.46	1.77	1.46	0.50
W12MC09	125	125	250	2234	8.9	14	0	0.77	1.31	1.08	3.23	3.15	0.50
W12NA01	340	80	420	24455	58.2	12	0	1.23	1.38	1.38	2.23	4.00	0.81
W12NA02	315	152	467	7929	17.0	13	22	0.62	0.62	0.23	1.92	1.46	0.67
W12NA03	125	125	250	1059	4.2	12	22	0.54	0.46	0.85	2.15	1.85	0.50
W12NA04	170	200	370	3708	10.0	12	4	0.62	0.92	0.62	2.15	2.15	0.46
W12NA05	100	150	250	3017	12.1	24	22	0.69	1.08	0.85	2.92	2.62	0.40
W12NA06	388	318	706	4069	5.8	12	25	0.46	0.85	1.46	2.69	2.77	0.55
W12NS01	500	400	900	164562	182.8	24	5	1.00	1.31	1.54	1.54	3.85	0.56
W12NS02	250	250	500	8376	16.8	24	0	0.46	1.08	0.69	1.85	2.23	0.50
W12NS03	300	242	542	24345	44.9	12	18	0.38	0.69	0.46	1.38	1.54	0.55
W12NS04	195	100	295	6206	21.0	12	10	0.69	0.77	0.62	1.31	2.08	0.66
W12NS05	500	250	750	53357	71.1	24	8	1.08	1.15	0.92	2.92	3.15	0.67
W12NS06	275	0	275	5026	18.3	12	0	0.38	0.77	0.38	0.92	1.54	1.00
W12NS07	350	330	680	3977	5.8	24	10	0.92	1.08	1.54	1.92	3.54	0.51
W12NS08	300	150	450	59078	131.3	24	5	0.77	1.23	1.46	2.23	3.46	0.67
F12AF01	41.5	20.5	62	153	2.5	24	3	0.54	0.92	0.92	3.54	2.38	0.67
F12AR01	305	305	610	6435	10.5	24	0	0.69	1.08	1.15	2.54	2.92	0.50
F12AR03	245	245	490	5121	10.5	24	8	0.85	1.00	0.69	3.31	2.54	0.50
F12AR04	405	405	810	9746	12.0	24	0	0.77	0.85	0.92	2.77	2.54	0.50
F12AR06	255	255	510	4715	9.2	24	11	0.69	1.23	1.00	3.15	2.92	0.50
F12AR07	250	250	500	12291	24.6	24	3	0.85	1.15	1.54	3.00	3.54	0.50
F12AR08	500	500	1000	21890	21.9	24	0	0.62	0.92	0.92	2.54	2.46	0.50
F12AR11	250	1000	1250	21914	17.5	24	0	1.08	1.38	2.08	2.85	4.54	0.20
F12AR12	500	500	1000	6100	9.8	24	11	0.77	1.08	0.85	3.31	2.69	0.50
F12AR14	375	375	750	6100	13.0	24	11	0.54	0.85	0.85	3.31	2.23	0.50
F12AR15	440	440	880	17534	19.9	24	0	0.69	1.08	1.31	2.38	3.08	0.50
F12NV01	400	75	475	9562	20.1	12	12	0.85	1.38	0.92	2.77	3.15	0.84
F12NV02	150	150	300	603	2.0	24	24	0.69	1.00	1.62	3.00	3.31	0.50
F12NV05	170	170	340	5887	17.3	18	18	0.77	1.31	0.92	2.92	3.00	0.50

- Prior year DEA runs were performed separately for weapon system projects and facility projects. In FY12, All projects were evaluated in a single DEA run.

Table 34. FY12 Combined Weapon System and Facility DEA Output Data – Blue shaded DMUs listed by priority*

DMU	Score	Rank	Reference set (lambda)							
F12AR11	1	38	W12AR09	9.71E-02	W12AR11	1.02E-03	W12AR12	0.491668		
W12AR09	1	37	W12AR11	0.534358	F12AR11	9.24E-02				
W12MC03	0.729569	43	W12AR09	0.153958	W12AR11	0.29363	W12AR12	3.34E-02		
W12MC09	0.785834	24	W12AR09	0.514971	W12AR11	0.212995	F12AR11	0.297783		
W12AF02	0.762065	13	W12AR09	0.177958	W12AR11	0.471538	W12AR12	0.118626		
W12MC04	0.613909	44	W12AR09	5.08E-02	W12AR11	0.508637	F12AR11	6.77E-03		
F12AR03	0.694261	25	W12AR11	0.501756	F12AR11	0.379898				
F12AR14	0.694261	1	W12AR10	1						
F12NV05	0.673121	7	W12AR10	7.53E-02	W12AR11	0.739073				
F12NV02	0.629679	41	W12AR11	0.255433	W12AR12	0.236371	F12AR11	0.123141		
W12NA06	0.626463	21	W12AR11	0.414475	W12AR12	0.106319	F12AR11	0.403707		
W12MC06	0.560403	48	W12AR10	6.43E-02	W12AR11	0.359645				
F12AF01	0.605157	10	W12AR11	0.834699	W12AR12	7.02E-02	F12AR11	0.413627		
W12MC02	0.814355	45	W12AR11	0.244729	W12AR12	8.66E-02	F12AR11	0.234402		
W12NS07	0.562404	22	W12AR11	0.466393	F12AR11	0.474215				
W12MC07	0.592307	34	W12AR11	0.436983	F12AR11	0.416743				
W12MC01	0.461051	6	W12AR09	0.706737	W12AR12	8.20E-02	F12AR11	0.397982		
W12MC05	0.612456	28	W12AR09	0.140277	W12AR11	0.371027	W12AR12	0.30431	F12AR11	0.10716
W12NA04	0.578767	31	W12AR11	0.430516	F12AR11	0.437737				
W12AR11	1	14	W12AR11	0.338376	W12AR12	2.23E-02	F12AR11	0.578042		
W12AR10	1	32	W12AR11	0.513648	F12AR11	0.118168				
F12NV01	0.563066	1	W12AR12	1						
W12NS08	0.626267	19	W12AR11	0.566674	W12AR12	2.43E-02	F12AR11	0.291663		
W12AR04	0.781642	30	W12AR09	0.228535	W12AR11	0.103833	W12AR12	0.295352		
W12AR05	0.706166	8	W12AR11	0.743735	F12AR11	0.210491				
W12NS01	0.84573	36	W12AR11	0.343778	W12AR12	0.104157	F12AR11	0.332184		
F12AR15	0.516185	1	W12AR11	1						
F12AR07	0.648184	15	W12AR09	8.95E-03	W12AR11	0.145238	W12AR12	0.597771	F12AR11	5.55E-02
W12NA05	0.713114	20	W12AR11	0.49031	F12AR11	0.498533				
F12AR01	0.532805	11	W12AR11	0.653695	F12AR11	0.34946				
F12AR06	0.66197	9	W12AR09	0.596954	W12AR11	0.196125	W12AR12	0.41779		
F12AR12	0.694261	1	W12AR09	1						
W12NS02	0.402566	1	F12AR11	1						
W12AR06	0.441824	12	W12AR10	0.228584	W12AR11	0.88862				
W12NA03	0.541079	16	W12AR11	0.514228	F12AR11	0.522852				
W12NS03	0.416427	16	W12AR11	0.514228	F12AR11	0.522852				
W12NS04	0.40346	16	W12AR11	0.514228	F12AR11	0.522852				
W12AR12	1	23	W12AR11	0.695359	F12AR11	8.14E-02				
W12AF03	0.756478	26	W12AR11	0.466286	W12AR12	4.26E-02	F12AR11	0.339101		
W12AR01	0.625314	27	W12AR11	0.50821	W12AR12	2.29E-02	F12AR11	0.420113		
W12NA01	0.744803	29	W12AR11	0.701263	F12AR11	0.371403				
W12NS06	0.282599	33	W12AR10	0.032111	W12AR11	0.812487				
W12AR02	0.357725	35	W12AR11	0.553442	F12AR11	9.57E-02				
W12NA02	0.388288	39	W12AR11	0.39464	F12AR11	0.401259				
W12NS05	0.605284	40	W12AR09	1.95E-02	W12AR11	0.344065	W12AR12	3.08E-02	F12AR11	0.360957
F12AR08	0.550934	42	W12AR11	0.509058	F12AR11	0.272138				
W12AR07	0.540553	46	W12AR09	2.16E-02	W12AR11	0.501492	W12AR12	3.24E-02		
F12AR04	0.581242	47	W12AR11	0.349431	F12AR11	0.241247				

- Projects listed in priority order and will be funded in that order until funds exhausted