A Complex Adaptive Systems Analysis of Productive Efficiency

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ABSTRACT

Linkages between Complex Adaptive Systems (CAS) thinking and efficiency analysis remain in their infancy. This research associates the basic building blocks of the CAS "flocking" metaphor with the essential building block concepts of Data Envelopment Analysis (DEA). Within a proposed framework DEA "decision-making units" (DMUs) are represented as agents in the agent-based modeling (ABM) paradigm. Guided by simple rules, agent DMUs representing business units of a larger management system, "align" with one another to achieve mutual protection/risk reduction and "cohere" with the most efficient DMUs among them to achieve the greatest possible efficiency in the least possible time. Analysis of the resulting patterns of behavior can provide policy insights that are both evidence-based and intuitive. This research introduces a consistent methodology that will be called here the Complex Adaptive Productive Efficiency Method (CAPEM) and employs it to bridge these domains. This research formalizes CAPEM mathematically and graphically. It then conducts experimentation employing using the resulting CAPEM simulation using data of a sample of electric power plants obtained from Rungsuriyawiboon and Stefanou (2003). Guided by rules, individual agent DMUs (power plants) representing business units of a larger management system, "align" with one another to achieve mutual protection/risk reduction and "cohere" with the most efficient DMUs among them to achieve the greatest possible efficiency in the least possible time. Using a CAS ABM simulation, it is found that the flocking rules (alignment, cohesion and separation), taken individually and in selected combinations, increased the mean technical efficiency of the power plant population and conversely decreased the time to reach the frontier. It is found however that these effects were limited to a smaller than expected sub-set of these combinations of the flocking factors. Having been successful in finding even a limited sub-set of flocking rules that increased efficiency was sufficient to support the hypotheses and conclude that employing the flocking metaphor offers useful options to decision-makers for increasing the efficiency of management systems.

DEDICATION

To my family for their patience and support throughout this long journey.

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1 Introduction

Somewhere between static, often linear control-theory systems science and chaos lies a world of “perpetual novelty” (Holland, 1995, p. 31) full of dynamic, non-linear patterns of behavior that form unexpectedly from many local, more simple component behaviors to benefit the system as a whole. Not yet a full featured science with eloquent mathematical principles and methodologies, complexity science relies heavily on metaphors and other analogies derived from nature. It is heavily dependent on computer science and on agent-based modeling and simulation (Holland, 1999). Yet its advocates are already claiming that its widespread adoption will fundamentally change the current approach to economic, sociological and technical analysis and may indeed change the very definition of these disciplines (Bienhocker, 2006). Adherents believe complexity science holds the key to unlocking the secrets of some of the most important forces on earth yet they are aware that its capabilities and benefits remain largely unknown, even among generally well-informed audiences (Miller and Page, 2007 pp. 214-218). In contrast, the study of the productive efficiency of systems is long lived. Spawned in the early industrial age (Taylor, 1911; Cobb and Douglas, 1928), advancing rapidly during and after World War II (Koopmans, 1951; Farrell, 1957) and being refined continuously ever since (Charnes, Cooper, and Rhodes, 1978; Cooper, Seiford, Tone, 2006) it has becomes a mature, well-respected yet still underused science. Based firmly on a well-defined Theory of the Firm (Henderson and Quandt, 1980) and a set of Axioms of Production (Vaneman and Triantis, 2003), the study of productive efficiency continues to advance to take full advantage of the latest advances in analytical sciences (Sterman, 2000), accounting for ever-increasing levels of complexity and enabling more insightful, more effective decision-making.

Linkages between complexity science and productive efficiency analysis remain in their infancy. This research is a first effort to identify and associate the basic building blocks of these two fields and to put in place a framework and a platform for continued research. From complexity science a point of entry has been selected, that is, a well-researched and well-documented complex adaptive systems (CAS) metaphor known as “flocking” (Reynolds, 1987). From the field of productive efficiency analysis an established, well-respected, yet evolving form of analysis known as Data Envelopment Analysis (DEA) (Charnes, Cooper, and Rhodes, 1978; Banker, Cooper and Rhodes, 1984; Cooper, Seiford, Tone, 2006) has been selected. This research identifies, associates, and fuses the key “building blocks” (Holland, 1995) of these two disciplines into a single methodology which will be called in this research the Complex Adaptive Productive Efficiency Method (CAPEM). This research establishes a methodological bridge between them by associating the building blocks of CAS (environments, agents, goals, rules, percepts, actions, etc.) with the building blocks of DEA (production possibility space, decision-making units, efficient frontier, inputs, outputs, technical efficiency over time and dynamic feedback). Within the CAPEM framework DEA “decision-making units” (DMUs) are represented as agents in the agent-based modeling (ABM) paradigm. Guided by simple rules, agent DMUs (ADMUs) representing business units of a larger management system, “align” (Reynolds, 1987) with one another to achieve mutual protection/risk reduction and “cohere” (Reynolds, 1987) with the most efficient ADMUs among them to achieve the greatest possible technical efficiency (use of inputs and outputs) in the least possible time. Employing a modified version of the NetLogo ABM platform (Wilensky, 1999), experiments are conducted using illustrative scenarios, findings are provided and conclusions made with respect to the research hypotheses. Included in the research is a specific management system, a set of deregulated electrical power plants, as a means of illustrating the nature and potential value of making these associations. Descriptions of ways to generalize on this exploratory approach are provided together with suggestions on a number of specific areas for very fruitful future research.

1.1 Purpose

The purpose of this research is to explore a complex adaptive systems approach to the analysis of management system productive efficiency. This research establishes a heretofore non-existent framework for representing and analyzing the emergence of patterns of productive efficiency. It is expected that this initial framework can aid continued research to better enable the decision-maker in the actual decision making process and in better describing the actual patterns of production observed in the real world.

It is the intent of this research to establish a conceptual and methodological bridge between CAS thinking, as defined by Holland (1999) and productive efficiency analysis, as defined by DEA, specifically for systems that can be classified as management systems. For this research, management systems include any enterprise in which a human or a board made up of humans actively guides the key incremental and longer term decisions of the enterprise. The enterprise may be public or private. The enterprise produces a physical product or a service. For these human decision-makers productive efficiency is a fundamental goal that guides decision making by minimizing resources used or maximizing physical outputs and/or services produced.

By treating management systems as human ecosystems rather than machines CAS recognizes the autonomous, goal-oriented, non-linear nature of human decision-making and recognizes the importance of the interactions among decision-makers in the evolution of a management system. As a result of this research, a bridge has been formed between deductive, control-theory base forms of efficiency analysis and the inductive complexity science based forms of productive efficiency analysis. By exploring this approach, this research enables decision-makers responsible for these systems and organizations to establish efficiency benchmarks, identify options and make policy choices in complex adaptive environments that result in the achievement of ever increasing levels of productive efficiency. Kernick (2002, p.i) states, "The emerging science of complex adaptive systems offers a complementary perspective on organizational analysis and is already finding an application within health care. The emphasis moves away from the features of normal science (analysis, prediction and control) to focus instead on the configuration of relationships among the system's components and an understanding of what creates patterns of order and behavior among them. The important features are connectivity, recursive feedback, diversity and the existence of self-ordering rules that give systems the capacity to emerge to new patterns of order."

1.2 Research Hypotheses

The specific research hypotheses for this research are as follows:

- Hypothesis 1: Increasing the level of adaptability (i.e., 0, 5, 10, 15, 20, 25) to each of the four factors of flocking (alignment turn, cohesion turn, separation turn and separation distance) (a.k.a., increasing the ability to adapt using each of the flocking factors individually) in each excursion of the experiment increases the population mean technical efficiency (PopMeanTE).
- Hypothesis 2: Increasing the level of adaptability (i.e., 0, 5, 10, 15, 20, 25) for some combinations of the four factors of flocking (alignment turn, cohesion turn, separation turn and/or separation distance) (a.k.a., increasing the ability

to adapt using a combination of flocking factors) in each excursion of the experiment increases the population mean technical efficiency (PopMeanTE).

- Hypothesis 3: Increasing the level of adaptability (i.e., 0, 5, 10, 15, 20, 25) for each of the four factors of flocking (alignment turn, cohesion turn, separation turn and separation distance) (a.k.a., increasing the ability to adapt using each of the flocking factors individually) in each excursion of the experiment increases the population mean time to the efficient frontier (PopMeanTTEF).
- Hypothesis 4: Increasing the level of adaptability (i.e., 0, 5, 10, 15, 20, 25) for some combinations of the four factors of flocking (alignment turn, cohesion turn, separation turn and/or separation distance) (a.k.a., increasing the ability to adapt using a combination of flocking factors) in each excursion of the experiment increases the population mean time to the efficient frontier (PopMeanTTEF).

Details associated with the experimental hypotheses are in Chapter 5 where an application is presented.

1.3 The Problem

Miller and Page (2007) point out that in an attempt to deal with the complexity of a modern management system, current methods of analysis require a series of assumptions that, even when artfully done, can lose their intuitive connection to the essential nature of these systems. Limitations on computing power, the lack of well-established concepts for describing complexity and the lack of supporting analytic tools have, until recently, forced analysts to use a range of overly-simplistic assumptions to describe and analyze systems and organizations. Simplifying assumptions have been made with regard to the independence of individual system components, the nature of the relationships among system components and most importantly the nature of the overall dynamic behavior of these systems. Traditional statistical analytic methods assume complete independence of system components, assume linear relationships among components and assume systems to be in an overall state of equilibrium. Evolving methods of analysis have sought to relax one or another of these assumptions and after doing so seek to determine the range of practical problems to which a variant of the traditional method can apply. The rigorous and artful use of these variants has produced significant insights to the analyst. A degree of success has been achieved using “system dynamics methods” (Sterman, 2000) to account for ever changing relationships among the system factors and to analyze the overall behavior of the system over time. This has led to a marked increase in the quality and the value of the analysis. The use of “stocks and flows” (accumulations and rates of change) have improved the usability of the system dynamics method by a wider audience. Yet, system dynamic methods assume the existence of a pre-determined or top-down form of control on the overall system behavior and rely on assumed cause and effect relationships which limit the granularity of the analysis and the confidence level the decision-maker can have in the derived results of the analysis. Imposing top-down controls on the system components limits an analyst’s ability to discover unexpected emergent behaviors that might present themselves in the analysis.

As part of this research, the incorporation into the analysis of the management system CAS methods of productive efficiency analyses provides an intuitive representation of goal seeking behaviors, such as risk avoidance, hedging or continuous improvement and the common internal rules of management, often called business rules. Given the development of the current CAS ABM concepts and tools, there is an opportunity to incorporate ecosystem metaphors, such as alignment with others who share these goals or cohering with others who adopt successful behaviors.

The inherent interactions and communication among actual decision-makers that in the real world lead to the emergence of patterns of successful collective management behaviors, are typically unrepresented. This research describes an investigation into the building blocks associated with the CAS paradigm that offer ways to explicitly represent goal seeking behaviors and represent the use of simple rules of thumb to guide decision-making in the context of perpetual novelty, as management systems pursue strategies for continuous improvement in their productive efficiency.

Complexity science and CAS agent-based modeling are evolving rapidly with an ever growing community of researchers, a maturing core of guiding principles and an expanding body of literature. CAS still lacks a unified theory to match the "control theory" of standard systems thinking nevertheless, there exits significant convergence on a set of complex adaptive thinking "building blocks," analytic methods and tools. Given the development of the current concepts and tools, there is an opportunity to bridge the gap between the analyses of productive efficiency and complex adaptive systems thinking. The problem now is that current methods of analysis of productive efficiency do not take advantage of the increased computing power or the current maturity of complex adaptive systems approaches. The challenge for this research is to carefully examine the field of productive efficiency analysis to identify its essential concepts and characteristics and determine if, when combined with the essential concepts of CAS thinking, they enhance the analytic communities ability to detect and analyze the patterns of efficiency and productivity exhibited by complex adaptive systems and organizations. Being able to examine the field of productive efficiency from the perspective of complex adaptive system thinking could enhance the ability of analyst and decision-makers to take into account the true nature of complexity in their systems and organizations.

1.4 Research Objectives

- To complement current forms of productive efficiency analysis by adding a CAS based form of analysis;
- To establish a bridge between the Data Envelopment Analysis form of productive efficiency analysis and Complex Adaptive Systems thinking;
- To demonstrate the value of agent-based simulation in the analysis of productive efficiency;
- To demonstrate the ability to generalize this research to a larger class of problems than is possible within the scope of this research;
- To identify appropriate topics for future research in this area

1.5 Organization of This Dissertation

Following this introduction Chapters 2 provides a summary of a literature search of both CAS and DEA. This chapter provides key conceptual descriptions of the essential building blocks of these two disciplines. Chapter 3 describes the association of these building blocks and the inferences made to form the CAPEM methodology. Chapter 4 provides a description of the use of Constrained Generating Procedures (CGP) notation and standardized descriptors (Holland, 1999) to describe and communicate the CAPEM mathematical formulations for the CAS ABM community. Chapters 5 presents a CAS ABM based experiment conducted to illustrate the application of this methodology. In this chapter what is shown is the ability to generate policy-options employing the CAS flocking metaphor and to describe conclusions of this research with respect to the experimental hypotheses and the research objectives. Chapter 6 describes an approach for the generalization of this research and recommendations for future research.

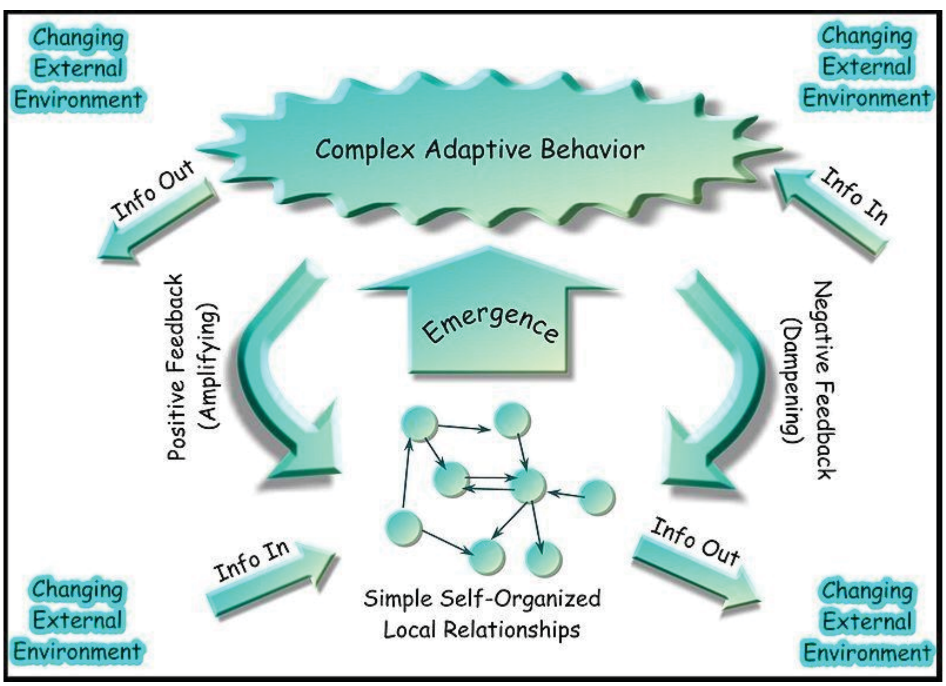
The dissertation includes four appendices. Appendix A provides summary descriptions of the CAPEM NetLogo-based code. Appendix B elaborates on the descriptions provided in Chapter 2, Literature Review, describing how CAPEM adheres to the DEA axioms of production. Appendix C provides additional information on the comparisons among the dynamic variations of Data Envelopment Analysis referenced in this research. Appendix D is a description of an agent-based formulation for an alternative productive efficiency method used by the US federal government known as the Kellogg Logic Model (Kellogg Foundation, 2004). It describes an early approach taken by employing the interactions among CAS agents to elaborate policy options for management systems.

2 Literature Review

2.1 Introduction to Complex Adaptive Systems Thinking

Figure 2-1, below illustrates the basic building blocks of CAS thinking. As described by (Andrus 2005, p.9) a management system is represented by the set of small circles (i.e., system/organizational elements and/or decision-makers) interacting constantly with their environment (political/organizational, economic, operational, and technical settings) and is characterized as a "simple, self-organized personal relationships" (i.e., information sharing, collaboration, competition). The system exists within an "[ever] changing external environment" represented below by the background field of the diagram. The thin arrows represent agent "communications" or "interactions." As indicated below, interactions among the agents and between the agents and their changing external environment result in the "emergence" of "complex adaptive behaviors."

Figure 2-1. Conceptual Model of a CAS (Andrus, 2005, p.9)



As indicated by the large upward pointing arrow in the center of the figure, the relationships among the agents and between the agents and between the agents and their changing external environment result in the emergence of complex adaptive behaviors, represented in the figure as a large star burst. Ronald, Sipper, and Capcarrere (1999) characterize this emergence as a set of “global behaviors and properties” whose “causal link” is “non-obvious”; that is, not anticipated based on knowledge of the existing, simple, self- organized, local relationships.

Finally, as illustrated below by the medium sized arrows emanating from the start burst, the complex adaptive behaviors, in turn, influence the ever changing external environment resulting in ever changing feedback to the agents themselves. A range of system-wide emergent behaviors can result. Some emergent behaviors lead more often to successful or desired outcomes than do others. Some emergent behaviors may not offer a successful approach to attaining desired or required goals. The CAS thinking form of analysis provides the decision-maker with the ability to sort among the range of possible system behaviors to determine those that, under the same or similar conditions will, with a higher degree of confidence, result in goal achievement.

Fundamental to CAS is the notion that each agent can be defined by a very simple, tractable set of internal goals and rules and that interaction among agents with even the simplest set of goals and rules exhibit perpetual novelty and result in very complex overall system behaviors (Holland, 1995). Holland explains that the perpetual novelty generated by the agents can result in “emergence,” which he defines as a pattern of behaviors that are true of the system as a whole but may not be indicated by the behavior of the sum of its components (Holland, 1999, p. 115). Some of these emergent behaviors serve to make the system better or more successful; many do not. By retaining the successful behaviors and discarding the others the system survives and grows (Holland, 1999). The evolving science of complexity is heavily engaged in finding systematic ways to identify these patterns of success and eventually in finding underlying principles and elegant mathematical equations that define patterns of complex behavior, much as the theory of relativity did for the laws physics.

2.1.1 Agent-Based Modeling: An Essential Element in Understanding CAS

Numerous authors are very clear about the value of agent-based modeling (ABM) in understanding CAS. Miller and Page (2007) go as far as to say that CAS analysis is not possible without ABM or whatever form of computational analysis that may take its place. Not only do computer simulations make it possible to visually represent a very large number of agents, they can record in the smallest detail, every interaction and every change in the state of every agent over time. Using modern computer power and newly developed simulation languages it is possible to experiment with innumerable starting conditions and vary the time horizon of the experiment in ways that would not be possible with other forms of experimentation. ABM enables efficient detection of patterns among the self-organizing local behaviors that arise from a large number of very simple system or organizational elements (Holland, 1999). Persistent, validated emergent behaviors in turn become the basis for experimentation and understanding of the next higher level of emergent behavior. A whole science is currently emerging around computational mathematics that will enable unprecedented levels of detail in the analysis of emergent behavior. While much remains to be understood about how complexity emerges from agents driven by such simple rules, the use of agent-based computer simulation enables the generation and capture of information at the level of detail needed to determine patterns that signal emergence (Miller and Page, 2007). Well-designed ABM experimentation provides a reliable means of determining leading indicators of successful behaviors and could offer decision-makers useful insights that could be used to improve efficiency of their management systems (Holland, 1999).

ABM enables more efficient detection of patterns among the self-organizing local behaviors that arise from a large number of very simple system or organizational elements (Holland, 1999). While easy to understand individually, the combination of their many interactions creates complexity and dynamics that the human mind cannot grasp much less use effectively. Fortunately, these patterns can be detected and analyzed in a mature ABM platform and can be shown empirically to forecast these self-organizing system behaviors (Holland, 1999). Persistent emergent behaviors become the components of increasing complex CAS ABM simulations. Properly modeled in ABM, CAS analysis can both employ previously determined patterns, such those used in weather forecasting and birds flocking and can discern new patterns that emerge from the current known patterns. Employed in these ways ABM simulation of management system elements over time and can lead to very useful leading indicators of system or organizational behavior, including measures of efficiency and to increasingly reliable analysis and decision-making. This research is presented in terms of both CAS ABM. Only when necessary are distinctions made between them.

2.2 The Building Blocks of CAS

2.2.1 The CAS Agent

Agents are a “special sub-category of open systems” (Bienhocker, 2006, p. 69) that will be called here, semi-open systems. They are like closed systems in that they have “boundaries”; that is, they are physically and conceptually distinct from their environment and all essential factors of the analysis necessary for decision-making may be contained inside their individual boundary. They have internal goals (i.e., become more efficient) and internal rules (i.e., avoid risk, employ best practices) that they use to determine their own internal "decisions" (i.e., use less fuel, employ fewer laborers). Agents can for their entire existences make decisions and exhibit behaviors (i.e., change location, direction or speed) without any inputs from outside their boundary. They are in this regard closed and statistically independent. Agents could also be considered open systems in that they "perceive"; that is, accept information or other inputs through their boundary. They also "act" or send information or other outputs into the environment or to other agents. Yet they are not statistically dependent because agents can select for themselves what they perceive and how they act. Agent perception and action are a function their own internal goals, rules and their own independent decisions. They do not depend on the information from outside their boundaries to continue to seek goals or follow their own rules. They will act according to their internal rules even if no additional information is forthcoming. Because there need not be a direct relationship between inputs and agent behavior agents are treated as semi-open systems and considered to be statistically independent. The word "autonomous" is used to describe them.

2.2.2 The CAS Environment

The CAS environment is treated as a "closed system." It must incorporate all essential factors of the analysis within the bounds of the system itself. The CAS environment is the medium in which the CAS agents interact. It contains all global resources including data, information and other variables necessary for agent operation. Distinction is made between the CAS environment and the CAS ABM simulation. The ABM simulation is the computer software application or platform written in a specific ABM capable language that, in addition to the representation of the CAS environment, includes the means of setting up and initializing an experiment as well as capturing and analyzing the results of the simulation.

2.2.3 Emergent Behavior and the CAS Metaphor

Presently, much of what is understood about CAS behaviors has been determined through observation of natural phenomena. Comparing man-made systems and organizational behavior to the behavior of ants, birds and fish, for example, has proven both insightful and practical (Reynolds, 1987; Johnson, 2001). Miller and Page (2007) cites the design of emergency exits on many new public buildings as an example. While it may seem counterintuitive to place a pillar in the path of a fearful crowd, new building exits now often incorporate a round pillar in the center of the corridor leading up to the exit. It has been learned through the study of termite swarming behaviors that doing so results in the formation of patterns of movement that increased the speed and volume of those exiting the constrained space, even under emergency conditions. (Fisher, 2009) in the book entitled, The Perfect Swarm, states that an increasing number of natural ecosystem-based patterns or metaphors have been rigorously defined, verified and validated against real world data and situations and are being applied to decision and policy making in fields as diverse as architecture, traffic control, disease control as well as program and project management. Wilensky (1999) provides an ever increasing list of CAS ecosystem metaphor-based simulations that are being assembled and validated for reliability across a spectrum of subject domains. Inherent to each metaphor are the goals, rules and the patterns of behavior, the emergent behaviors that have been shown over time to lead most often to goal achievement. Employing these metaphors in the appropriate circumstances and under the right conditions informs real world analysis and decision-making in management systems. By study and analysis of the system/organizational behaviors and close comparison with selected CAS metaphors a match may be determined, resulting in significant analytic insight and useful policy choices. For purposes of this research CAS flocking metaphor has been selected for analysis of the productive efficiency of complex systems and organizations.

2.2.3.1 The CAS Flocking Metaphor

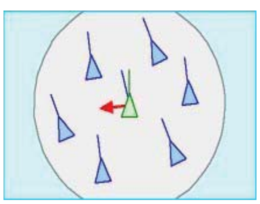
Tanner, Jadbabaie and Pappas (2003, p.1) state, “Over the last few years, the problem of coordinating the motion of multiple autonomous agents has attracted significant attention.” Problems related to coordinated motion among autonomous agents have been studied in ecology and theoretical biology, in statistical physics and complexity theory, in dynamical non-equilibrium phenomena, as well as in distributed control of multiple vehicles and formation control (Tanner, Jadbabaie and Pappas, 2004). Researchers from many different communities have been developing an ever deeper and richer understanding of how a group of agents can coordinate their behaviors to achieve a goal using only a small number of simple rules and local interactions, and do so without a global supervisor.

Reynolds (1987) explains that flocking behaviors in nature are understood to achieve the goal of collective protection while foraging. To a predator the large formation appears to be a larger bird or animal, something to be avoided, thus protecting the individual members of the flock Individual birds have no concept of the collective, only of their individual need for food and their individual need for protection while foraging. Studies of these formations have shown that none of the individual birds lead the flock or exercise direction or control over other birds. Each is autonomous, coordinating its motion with the flock to achieve only its individual goals. Figure 2-2 below displays a snapshot in time of a generic NetLogo flocking simulation (Wilensky, 1999), where the superposition of three simple rules results in all agents moving in an assortment of small formations, while avoiding collision.

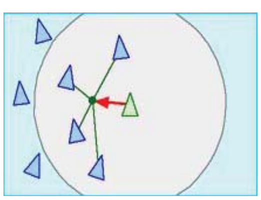
Figure 2-2. Simulation of Flocking Behavior

Reynolds (1987) is the most commonly referenced computer model for this form of coordinated motion. Reynolds was able to simulate the naturally emergent flocking behavior of birds, swarms of fish, bats and other naturally occurring coordinated motion by modeling autonomous agents with the following three simple, internal steering rules:

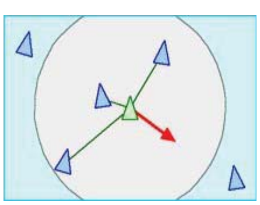
Figure 2-3. The Steering Rules of Flocking (Reynolds, 2001, p.1)



Alignment: steering to match the average of the headings being taken by selected local flockmates



- Cohesion: steering toward the average of the positions or current locations of selected local flockmates



- Separation: steering to avoid crowding to other nearby members of the flock

In Reynolds' early model, each agent was required to access the entire geometric description of the environment and all members of the flock. Later models incorporated the ability to react only to flockmates within a certain small neighborhood around itself. Tanner, Jadbabaie and Pappas (2003) demonstrated that flocking occurs when each agent is self-guided using state information from a fixed set of interconnected neighbors. Tanner, Jadbabaie and Pappas (2004) later showed that flocking can also occur when the pattern of interactions is dynamic and that simulation of distance-based dynamic agent interactions guaranteed collision avoidance, regardless of the structure of the interactions among agents. Both

Reynolds' and Tanner's research further showed that agents may switch among "flockgroups." Tanner, Jadbabaie and Pappas (2004) validated the use of the flocking metaphor for systems in transition through a variable increment of time. His analysis combines results from classical control theory, mechanics, algebraic graph theory, non-smooth analysis to show that while using the alignment, cohesion and separation elements of the flocking metaphor all agent velocities converge to the same vector and all pair-wise distances are stabilized.

This flocking metaphor was chosen for this research both for its conceptual similarity to the coordinated behavior of a management system and because it has been so well defined, so thoroughly studied and validated. The depth of understanding of the emergent behavior of flocking and its inherent goals, rules, percepts and actions make it a prime choice for this initial research and for increasingly sophisticated implementations of this research in the future.

2.2.3.2 Applicability of the CAS Flocking Metaphor to Production Behavior of Management Systems

The metaphor is well-suited to the analysis of efficiency for a number of reasons.

First, it has wide acceptance as a validated model of emergent behavior. Rising above the on-going debate in complexity science about the nature and definition of emergence, flocking is, by consensus, among the first metaphors to be widely accepted and widely used. Second, as described above, Reynolds' rules of flocking (alignment, cohesion, separation) have proven robust under a wide range of conditions and now has well-refined, rigorous mathematical formulations of both fixed and dynamic relationships among the flockmates. Third, the flocking of birds is widely observed in nature and is intuitive as a metaphor to a large number of audiences.

The associative inferences that can be made between flocking and the goal seeking, risk avoidant behaviors of a management system are numerous. Whether, for example, it is a set of autonomous power plants or a set of public or social service organizations, all management systems deal with the issue of risk and risk mitigation. Just as birds seeking protection wisely move in the same general direction or align with other birds for protection from predators and other threats, individual power plants would be wise to align with accepted industry best practices, especially the best practices of other power plants similar to themselves. By doing so, individual power plants avoid making catastrophic errors in decision-making while at the same time seeking to achieve increasing levels of operational efficiency.

Just as birds move toward the locations of those birds that most efficiently find food, individual power plants would, in the terms of the flocking metaphor, be wise to cohere with or otherwise seek to emulate the policies and practices of the most efficient members of their respective industry. As they align and cohere with their flockmates however, birds must avoid colliding into one another. Just as birds maintain appropriate "separation" from one another a management system would be wise to avoid colliding with its nearest flockmates in terms of the use of scarce resources. Neighboring, power plants, for example can avoid inflating their own costs by not competing for the same labor pool, or the same raw materials. Depending on the nature of the industry there are numerous forms of danger that should be avoided by an individual management system as it attempts to achieve common efficiencies.

Another analog is the flocking metaphor representation of the nature of the communication among birds and the nature of the influence of one bird on another. In the flocking metaphor the number of flockmates that can be observed by an individual bird is analogous to the number of other power plants that any one power plant is able to communicate with for information or assistance. This number might include the entire population of power plants or a very small sub-set. In the flocking metaphor the nature of the communication among individual agents may vary. Birds observe one another visually while bats sound range to determine their distance and speed from other bats in a swarm. This contrast is analogous to variations in the type and amount of information shared among power plants. Power plants belonging to a single corporation might share significant levels of information and data. Power plants in competing corporations might know only as much about one another as is publically available. The analog between the flocking behaviors of ecosystems in nature and the corporate behaviors of ecosystems in business are many and varied. These comparisons and others could become increasingly evident and increasingly mature as building blocks of CAS are added to the building blocks of efficiency.

In nature, individual small birds seek to avoid the risk of being attacked by larger predatory birds as they forage. Flocking is their risk mitigation strategy. Foraging for food as described by Fisher (2009) is also more efficient when accomplished by a large number of birds, fish or bats that can collectively encounter sources of food over a larger area. Just as birds seeking protection wisely move in the same general direction or align with other birds for protection from predators and other threats, individual power plants would be wise to align with accepted industry best practices, especially the best practices of other power plants similar to themselves. By doing so, individual power plants avoid making catastrophic errors in decision-making while at the same time seeking to achieve increasing levels of operational efficiency. Just as birds move toward the locations of those birds that most efficiently find food, individual power plants would, in the terms of the flocking metaphor, would be wise to cohere with or otherwise seek to emulate the policies and practices of the most efficient members of their respective industry.

As they align and cohere with their flockmates however, birds must avoid colliding into one another. Just as birds maintain appropriate “separation” from one another a management system would be wise to avoid colliding with its nearest flockmates in terms of the use of scarce resources. Neighboring, power plants, for example can avoid inflating their own costs by not competing for the same labor pool, or the same raw materials. Depending on the nature of the industry there are numerous forms of danger that should be avoided by an individual management system as it attempts to achieve common efficiencies.

The useful analogs between the flocking metaphor and a management system go still deeper. The implementation of these rules of flocking used for this research includes, for instance, measures of an agent’s ability to change its alignment, cohesion or separation in a given increment of time (Wilenski, 1999). These equate to the maximum and minimum ability of a power plant to make necessary changes, to adapt. Just as birds have limits in their ability to change direction, power plants are limited in the nature and speed with which they can achieve change.

Another analog is the flocking metaphor representation of the nature of the communication among birds and the nature of the influence of one bird on another.

In the flocking metaphor the number of flockmates that can be observed by an individual bird is analogous to the number of other power plants that any one power plant is able to communicate with for information or assistance. This number might include the entire population of power plants or a very small sub-set. In the flocking metaphor the nature of the communication among individual agents may vary. Power plants belonging to a single corporation might share significant levels of information and data. Power plants in competing corporations might know only as much about one another as is publically available.

Management system strategy is by definition a description how senior corporate leadership would like the system to behave to achieve its goals and accomplish its mission (Gryna, Chua, and Defeo, 2007). Ideally, individual and collective decisions align with this description and execute the strategy. For this research, the CAS metaphor of flocking was chosen to represent the aspect of management system strategy that deals with cross-corporation coordinated decision-making. The rules of flocking, alignment, cohesion and separation then become the principles or business rules that guide individual component decision-making. These associations and inferences that can be made from them for this research will be further elaborated in Chapter 3 of this dissertation.

2.3 Building Blocks of the DEA Form of Productive Efficiency Analysis

2.3.1 Standard DEA

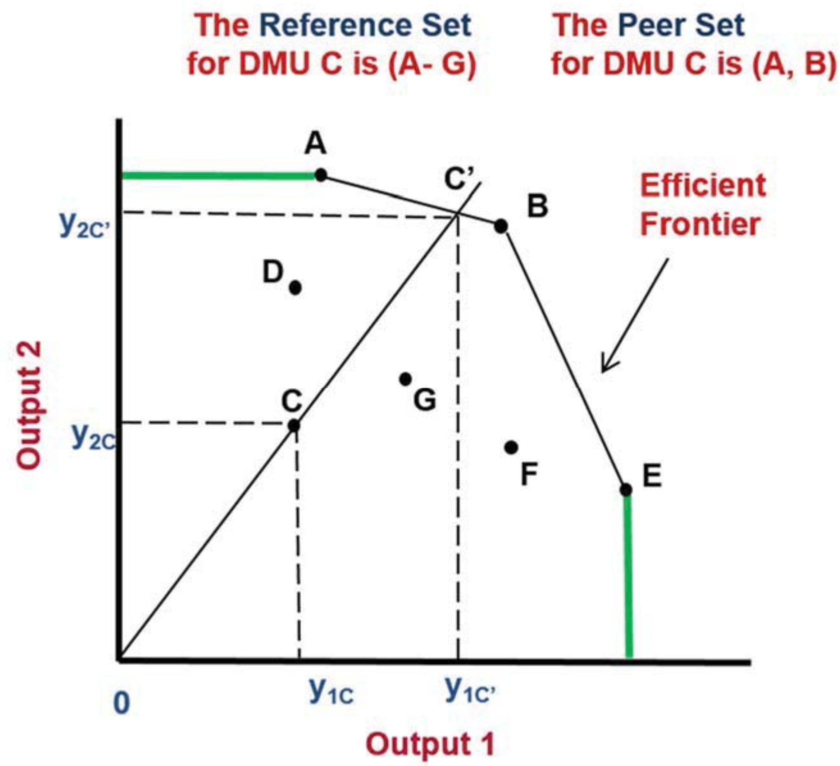
To identify the building blacks of productive efficiency for this research we chose to employ a well-respected form of productivity analysis know as Data Envelopment Analysis (DEA) (Koopmans, 1951; Farrell, 1957; Charnes, Cooper and Rhodes, 1978). In addition to its respected place among traditional forms of productivity analysis, DEA has the advantage of having recently been extended to include dynamic, non-linear formulations (Färe, 1995; Vaneman and Triantis, 2004). This recent extension of DEA, known as Dynamic Productive Efficiency Modeling (DPEM) together with its standard DEA antecedent will be used in this research to identify the building blocks of productive efficiency analysis that will enable the extension of DEA into the world of complex adaptive systems thinking.

Standard DEA is a non-parametric optimization approach that computes the relative efficiency of firms, organizations, or systems in which there are multiple inputs and/or multiple outputs, and in which, it is desirable and possible to aggregate the inputs or outputs into a single measure of relative efficiency (Charnes, Cooper and Rhodes, 1978). Firms, organizations, or systems are treated as single entities known as "decision making units" (DMUs). DEA provides an approach to identifying the most efficient among a population of similar DMUs and uses them to make benchmark comparisons, guide policy and decision-making. The objective of DEA is to optimize the efficiency of a population of DMU and provide each DMU a means of determining policies for becoming more efficient.

2.3.1.1 Factors of Production and the Production Possibility Space

Figure 2-4, below, illustrates graphically the basic building blocks of standard DEA. Each axis represents a "factor of production," which in the two dimensional output space below are Outputs 1 and 2. The axes of the coordinate scale delimit the "productive possibility space" (PPS).

Figure 2-4. The Building Blocks of Standard DEA



While graphical representations of inputs and outputs are, of course, limited generally to two or three dimensions, DEA can readily calculate values for multiple inputs and multiple outputs.

2.3.1.2 Decision-Making Units and the Efficient Frontier

Systems and organizations are represented individually above as DMUs, each having a lettered (A-F) positions (*y*, *y*), (*x*, *x*) or (*x*, *y*) in the PPS. Only DMUs that have common characteristics (goals, inputs, outputs) and similar circumstances (common market, common technology, common volumes and scale of operations)" should be compared. This set of DMU is known as the "reference set" (Cooper, Seiford and Tone, 2007).

The piecewise linear curve traversing the PPS is known as the "efficient frontier" (EF). In a two dimensional space, it is defined by connecting with straight lines, the most efficient among the family of DMUs. In this illustration, these are the upper most and right most DMUs in the population of DMUs (A, B and E). The efficient frontier indicates, in this case, the line of output efficiency achievable for this family of DMUs. The set of efficient DMUs are known as the "peer set." The efficient frontier is effectively a "benchmark" that can be used by decision-makers to identify "options" and modify "policies." To become efficient the less efficient DMUs would pursue policies that would bring them ever closer to a point on the efficient frontier between two members of the "peer set."

2.3.1.3 Productive Efficiency and the Production Function

Productive efficiency is defined as the simple ratio shown below (Boussofiane, Dyson and Thanassoulis, 1991).

Equation 2-1. $$\text{Efficiency} = \frac{\text{Weighted Sum of Outputs}}{\text{Weighted Sum of Inputs}}$$

This is a very basic, intuitive definition of efficiency which can apply to many forms of production systems be they systems that produce chemicals, electrical power, retail manufacturing, or produce services such as healthcare and education.

DEA then expands on this simple definition to enable management system decision-makers to consider multiple inputs and multiple outputs. Since DMUs usually have more than one input and output, the simple ratio above is expanded to (Boussofiane, Dyson and Thanassoulis, 1991):

Equation 2-2

$$\theta_k = \frac{\sum_{r=1}^{M} u_r\ y_{r0}}{\sum_{i=1}^{N} v_i\ x_{i0}}$$

Subject to:

$$\frac{\sum_{r=1}^{M} u_r y_{rj}}{\sum_{i=1}^{N} v_i x_{ij}} \leq 1 \qquad j = 1,2, \ldots., n$$

$$u_r\ v_i \geq 0;\ r = 1.2, \ldots., m;\ = 1.2, \ldots., m;$$

Where:

θ_k – the objective function or the measure of productive efficiency
u_r – weight given to output r v_i – weight given to input i y_{rk} – the amount of output r from the unit k x_{ik} – the amount of input i from the unit k n – number of units m – number of outputs
n – number of inputs

Weighted sums of doctors and nurses, for example, produce weighted sums of patients who have been treated and released from the hospital at various levels of health. Under similar circumstances one hospital may treat and release more patients with a greater level of health than another hospital. The first is more efficient than the second. Using the weighted sums of doctors and nurses as inputs and weighted sums of treated patients at various levels of health as outputs it is possible to gain insight into the patterns of productive efficiency and policies that might be available to less efficient hospitals to make improvements.

Since the optimum weights of the inputs and outputs are generally unknown, the previous equation is further refined by (Charnes, Cooper and Rhodes, 1978) into a model based on principles of linear programming that consider the unknown weights and solves the model for its maximum possible values.

In the above equation the system is maximized to attain the maximum possible value of productive efficiency for each DMU. Since each DMU is being given the maximum possible efficiency rating (as opposed for example, an efficiency rating based on a measure of central tendency), it can be judged as being efficient or being truly inefficient when compared to the most efficient DMU(s) (Charnes, Cooper and Rhodes, 1978).

2.3.1.4 The DEA Production Function

The relationship among the factors of production is known as the production function (PF). Färe and Lovell, 1978, define the DEA production function as a scalar output that specifies the maximum output obtainable from an input vector. Thus the production function describes a technical relationship between the inputs to the production process and the outputs from the production process.

The PF is the standard DEA mathematical construct that derives from an underlying theory of firm and its axioms of production. Based on empirical studies and data the PF precisely defines the relationship between inputs and outputs for a given subject domain and population and often takes the form of a (Cobb and Douglas, 1928) equation such as:

Equation 2-3 $$Q = 0.049K^{.25}\,L^{.1}F^{.7}$$

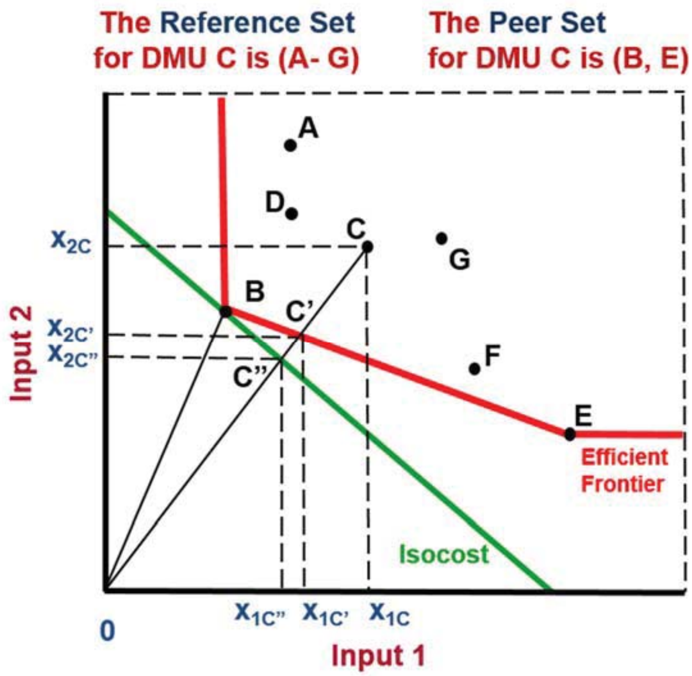
Q (electrical energy) is the output and K (capital), L (labor) and F (fuel) are the inputs or factors of production. The weights and exponents are derived from empirical data developed through extensive experimentation and analysis. Standard DEA formulations most often take the form of a series of linear equations and enable the decision-maker to either maximize outputs for given levels of inputs or minimize inputs for a given level of outputs.

2.3.1.5 Technical Efficiency

Technical efficiency (TE) reflects the firm's physical ability to produce the maximum output for a given input. If this condition is met, the unit is said to be operating on its production frontier. A technically inefficient unit will be operating below the production frontier, thus it is not optimally using its inputs to produce outputs (Farrell, 1957) (Coelli, Rao, and Battese, 1998). The efficiencies of all agentDMUs are calculated and normalized to enable direct comparisons. The most efficient agent DMUs are identified and become the standard to which others are compared. Once calculated and normalized inefficient agent DMUs can then compare themselves to the most efficient agent DMUs and make choices about how to become more efficient. While this research focuses only on technical efficiency, for completeness it is necessary to point out that standard DEA provides the means of making comparisons in the form of not only "technical" efficiency but "allocative" or cost efficiencies and a measure of overall efficiency described below. As TE characterizes the physical efficiency of transforming inputs into outputs. Allocative efficiency characterizes the economic or price efficiency associated with transforming inputs into outputs (Farrell, 1957).

Figure 2-5 below, represents a reference set of DEA DMUs at a single point in time, on a plane representing the relationship between two relevant inputs (i.e., labor and fuel).

Figure 2-5. DEA Building Blocks of Technical and Allocative Efficiency



This approach allows for the analysis of efficiency by comparing the measured values with respect to an optimal technical and optimal cost point indicated by point B in Figure 2-5 above. A DMU that lies on the efficient frontier is deemed technically efficient. A DMU that lies at the isocost line is deemed allocatively efficient (AE). A DMU that lies at the intersection of the efficient frontier and the isocost lines is deemed overall most efficient. The mathematical relationships for technical efficiency, allocative efficiency, and overall productive are as follows (Farrell, 1957):

TE is mathematically defined as: $\overline{OC}/\,\overline{OC'}$ Equation 2-4

AE is defined as: $\overline{OC}/\,\overline{OC''}$ Equation 2-5

Overall productive efficiency (OPE): (TE) x (AE) Equation 2-6

2.3.1.6 Decision-Making

Formulations exist that enable maximizing outputs for given levels of inputs or minimize inputs for a given level of outputs (Boussofiane, Dyson and Thanassoulis 1991), the so-called envelopment forms. DEA then provides two basic ways to approach decision-making for purposes of achieving the optimal technical efficiency. These two basic approaches and their numerous variations implement an underlying "Theory of the Firm" (Hendersen and Quandt, 1980; Graig and Harris, 1973), and a set of "Axioms of Production" as described by Boussofiane, Dyson and Thanassoulis (1991) and Vaneman and Triantis (2003).

Figure 2-6a. Standard DEA Output Maximization Policy

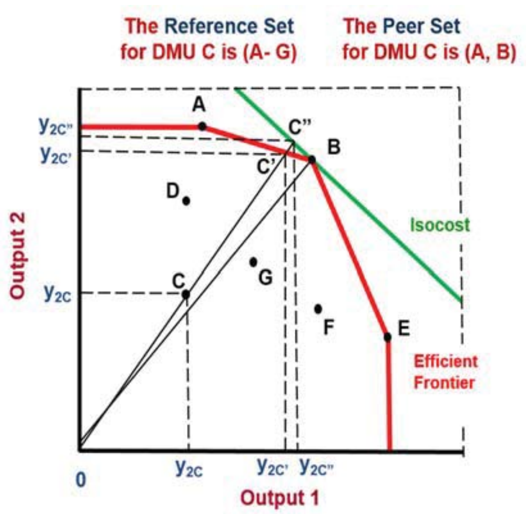
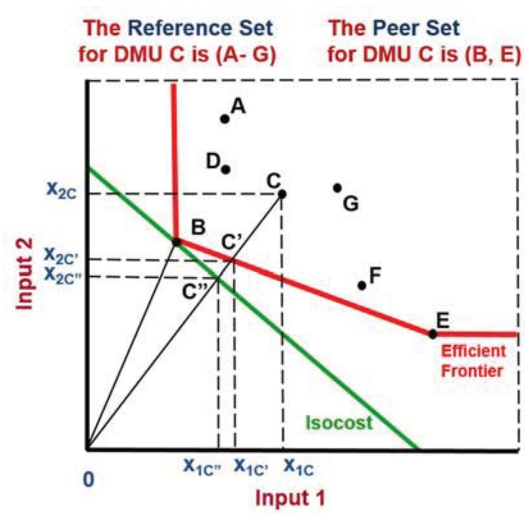


Figure 2-6b. Standard DEA Input Minimization Policy



In standard DEA, the analysis of productive efficiency takes on one of two primary approaches, which conform to the two most intuitive ways in which efficiencies can be realized. A system or organization, a DMU, can seek to maximize the level of output achieved for a given set of inputs or minimize the inputs required to achieve a given level of output. The linear programing formulation of the "output maximization" approach is expressed as:

Equation 2-5

$$\mathrm{Max}_z\ \theta$$

$$\sum_{j=1}^{n} z_j x_{ij} \leq x_i^0 \,, i = 1.2, \ldots . m$$

$$\sum_{j=1}^{n} z_j y_{rj} \geq \theta y_r^0 \,, r = 1.2, \ldots . t$$

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

Note that the objective function representing output is being maximized subject to several constraints. These constraints ensure that the optimum solution conform to some basic physical laws, known in DEA as the “axioms of production.” The first constraint requires two things, first that there must be some level of input to produce an output and that the weighted sum of the inputs used by the reference set DMUs not exceed the initial amount available. This is generally known as the “no free lunch” axiom. The second constraint requires that the weighted sum of outputs among the reference set must be at least as great as the initial outputs of its members times a maximized factor of production. The third constraint requires that the sum of the weight be added to one in which in terms of physical laws means that the relationship between outputs and inputs remains the same during production regardless of the scale of the production. This is known in DEA as a “constant return to scale.” Summing to something other than one would mean that the relationship between outputs and inputs would change as the number of units produced changed. The optimization problem would need to be treated as a special “variable returns to scale” case, beyond the scope of this research.

The second primary DEA approach to analysis of productive efficiency is the “input minimization” approach. The linear programming formulation of which is expressed as:

Equation 2-6

$$Min_z \theta$$

Subject to:

$$\sum_{j=1}^{n} z_j \, x_{ij} \leq \theta \, x_i^0, \quad i = 1.2, \ldots, m$$

$$\sum_{j=1}^{n} z_j \, y_{rj} \geq \; y_r^0, \quad r = 1.2, \ldots, t$$

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

Note the similarity as well as the contrast in the constraints. In this second primary DEA approach the sum of the weighted inputs is required to be less than or equal to the initial level of inputs times a factor of minimized production. The second constraint requires that there not be a reduction in output produced. The constant return-to-scale constraint remains in place.

As stated above, standard DEA employs the linear programing formulations approach with their objective function and constraints to embody concepts of productive efficiency that conform to basic physical laws and known patterns of production known in DEA referred to above as the axioms of production. CAS approaches to measuring productive efficiency do not use linear programming techniques of analysis. In place of linear programing CAS employs mathematical formulations that represent a selected CAS metaphor, in the case of this research that metaphor is the flocking metaphor. It remains to be shown in this research that the CAS flocking formulations mapped to the DEA efficiency space likewise adhere to the DEA axioms of production. The axiom of production will be addressed further in a later section of the paper.

2.3.2 Dynamic DEA

Each of the building blocks described above for both CAS and DEA become items of investigation and are included in the CAS ABM simulation. However, because standard DEA models are static, single snapshots in time, it is necessary to also look at dynamic extensions to determine possible additional building blocks that will assist this research.

2.3.2.1 Incorporating the Element of Time

Färe and Grosskopf (1996) developed a form of dynamic data envelopment analysis (DDEA) by extending the standard DEA model into an infinite sequence of static models or snapshots in time. While this methodology does evaluate organizational performance over time, it assumes that the change in productive efficiency during each interval of time can be explained in simple, linear functions, meaning that there is no change in the rate of change or no complexity in the pattern of productive efficiency from one snapshot to another. The DDEA also uses outputs from one time period as inputs to the next time period, when in fact, the inputs to the next period of time may not be dependent at all on the state of the system at the end of the last period of time. No new building blocks of DEA are provided by DDEA however, an understanding of this approach further illuminates an understanding of DEA and indicates the need for extensions of DEA to represent the generation of non-deterministic, non-linear behaviors over time.

In developing DPEM Vaneman and Triantis (2003) examined the various ways in which dynamic systems were represented mathematically. Among the major theoretical constructs only the dynamical, causal, and closed systems construct allowed for examination of systems in a non-steady state condition during the period of transition and enable the analyst to influence the system behavior in the transition period. With this construct comparisons will be made with CAS flocking behaviors.

In both the CAS flocking metaphor and dynamic, causal, closed systems, behaviors are modified by introducing inputs via internal feedback mechanisms. DPEM extension of DEA productive efficiency in these systems is expressed as:

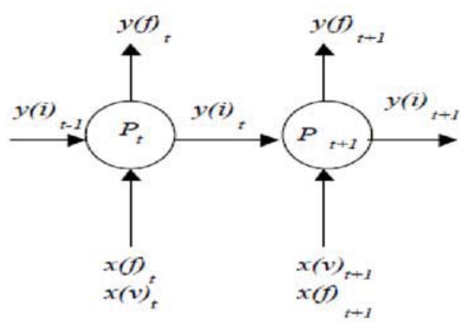
Equation 2-7. $$y_{jt} = f\{t\text{–}t_0; x_{it0}; x_{itd}; y_{j(td\text{-}t0)}\}$$

Where the final element of the output function, $y_j(t_d, -t_0)$, is the j^{th} output resulting from behaviors during the interval (t_0, t_d) or the output resulting from behaviors that began at the beginning of the time increment to the current point of measurement. By including the output resulting from behaviors up to the current point of measurement the DPEM approach to productive efficiency incorporates results from past actions and enables them to influence future actions. In systems dynamics this is done via an explicit feedback mechanism. Vaneman and Triantis (2004) also confirmed that including the time increment into the output variable was valid for each of the axiom of production.

It is this concept of including changes within the time increment and the output variable and incorporating the results from past or even external actions in the measure of productive efficiency that makes possible to understand the extension of DEA into CAS flocking behaviors with respect to time. The CAS flocking metaphor does not employ explicit feedback mechanisms for these time variables but inherent in "flocking" alignment, cohesion and separation is time dependent agent communication that likewise incorporates the effects of changes in previous increments of time to influence current behaviors.

Figure 2-7, below (Fare and Grosskopf, 1996), illustrates the concept. At each step of the sequence is a cycle of production, P_n. The optimum values for outputs at each cycle are calculated using the standard linear programming solution. The outputs from a previous production cycle exit the system or become inputs to the next cycle. This assumes that as a system changes over time it somehow remains in a stable, steady state condition. It does not account for very important dynamic behaviors that occur as a system transitions over time and between these snap shots in time. DDEA also uses outputs from one time period as inputs to the next time period when in fact the inputs to the next period of time may not be dependent at all on the state of the system at the end of the last period of time.

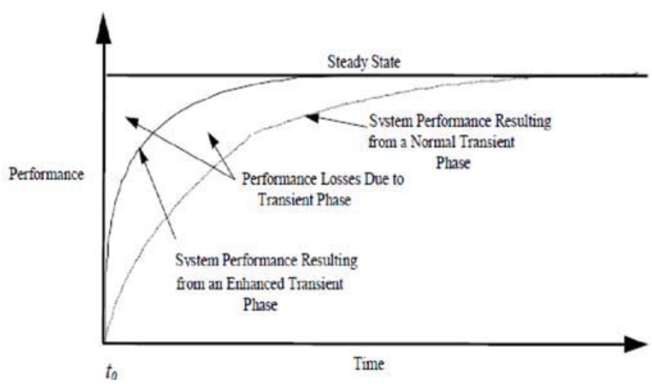
Figure 2-7. Dynamic DEA – Basic Structure (Vaneman and Triantis, 2007, p.54)



No dynamic behaviors are actually involved, only a series of static, linear behaviors recorded as snapshots in time. In the absence of dynamic behaviors and a multiplicity of ever changing interactions among DMUs, perpetual novelty (complexity) does not exist. Without perpetual novelty there is no possibility of the emergence of patterns of successful system behavior.

Other approaches have been taken to incorporate dynamic, non-linear, nondeterministic behaviors over time. Among these is the DPEM approach (Vaneman and Triantis, 2007). DPEM as described by Vaneman and Triantis (2003) is a system dynamics (Sterman, 2000) based approach that extends DEA to enable analysis of system behaviors that occur within these increments of time and does not assume steady state throughout. By incorporating levels of accumulation of products, flows or rates of change of inputs, active reinforcing and balancing feedback loops over time using Systems Dynamics (SD) modeling techniques (Sterman, 2000) they generated and analyzed many non-linear, non-deterministic results. Figure 2-8, below, illustrates the added understanding and value of doing so. In this figure the horizontal line at the top of the illustration represents the efficiency that would be calculated using the standard DEA and DDEA methods. This calculation would overestimate the efficiency of the system in this period of time and would offer no opportunity for improving performance.

Figure 2-8. DPEM System Performances Between Steady States
(Vaneman and Triantis, 2007. P.56)



If, for example, the true normal dynamic transient state for this time period is a form of exponential growth, as indicated by the lower curve, there would in fact be room for improvement. Deeper knowledge of the complexities of the system would lead to meaningful enhancements and increased efficiencies, as indicated by the upper curve. DPEM in contrast to DDEA illustrates the advantage of incorporating continuous, non-deterministic, non-linear behaviors over time as a building block of DEA analysis and offers an intermediate step toward addressing change over time as an element of complexity in the analysis of productive efficiency.

2.3.2.2 Dynamic Equilibrium and Stability

The DPEM extension of DEA points to another essential building block of productive efficiency analysis that is the ability to represent and analyze equilibrium or instability (disequilibrium) of the system.

A system in dynamic equilibrium is a system where there is a stable, non-oscillating flow of inputs and outputs throughout the system. Components of the system may themselves be in equilibrium or in flux. Viewing the system from a macro level, dynamic equilibrium gives the appearance that nothing within the system changes over time. A closer look reveals that there is a constant flow of inputs into the system, and a constant flow of outputs from the system (Sterman, 2000). All derivatives will have non-zero values for dynamic equilibrium. An example of a system in disequilibrium is a manufacturing plant where there is a constant influx of orders, and the number of orders exceeds the plant capacity. In this case the queue of orders will continue to grow. The disequilibrium will lead to instability and potentially undesirable consequences.

When a disturbance is introduced a previously stable system will generally experience at least temporary disequilibrium. Consider a small disturbance introduced to the system at time td. If the system returns to its original (or closely related) state of equilibrium after being disturbed, the system is considered stable (Frisch 1935; Sterman, 2000). If the small disturbance forces the system further away from equilibrium with the passage of time, the system is said to be in unstable equilibrium.

These definitions are essential in understanding the dynamics of efficiency and are therefore building blocks of DEA. CAS are said to exist somewhere “between equilibrium and chaos” (Miller and Page, 2007, p. 222). Understanding the concepts of equilibrium and stability will be essential CAS building blocks enabling us to associate and analyze the changes in productive efficiency over time.

The next part of the DPEM extension enables the analyst to understand the non-steady state nature of the system during transition. For definitions of these concepts Vaneman and Triantis (2004) employed the system dynamics paradigm (Sterman, 2000). The same definitions can be employed to gain a deeper understanding of CAS flocking behaviors. In the SD paradigm systems are categorized as being in equilibrium or in disequilibrium, stable or unstable. Equilibrium can be further categorized as either static or dynamic.

Static equilibrium is defined as the condition that exists when there is no flow or no change in behavior within the system. Two conditions must be satisfied for a system to be in static equilibrium: (1) all first order derivatives ($\dot{x}_{\mathrm{it}}$, $\dot{y}_{\mathrm{jt}}$) are zero at the time considered and (2) all higher order derivatives are also zero. A system in which only condition (1) is satisfied is said to be momentarily at rest (Frisch, 1935).

A system in dynamic equilibrium is a system where there is a constant flow or a constant rate of change going through the system. Viewing the system from a macro level, dynamic equilibrium gives the appearance that nothing within the system changes over time. A closer look reveals that there is a constant flow of inputs into the system, and a constant flow of outputs from the system (Sterman, 2000). All derivatives will have non-zero values for dynamic equilibrium.

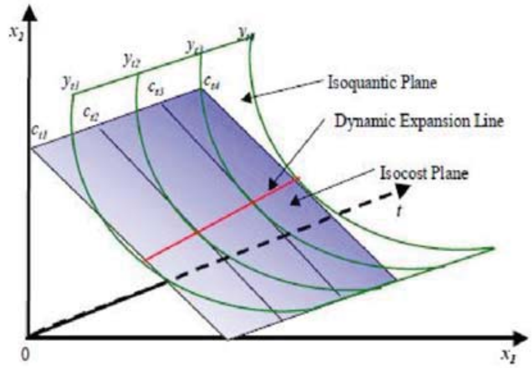
A system that does not meet the criteria for either static or dynamic equilibrium is said to be in a state of disequilibrium (Frisch, 1935). An example of a system in disequilibrium is a manufacturing plant where there is a constant influx of orders, and the number of orders exceeds the plant capacity. In this case the queue of orders will continue to grow, thus creating a state of disequilibrium.

System stability refers to how a system that was previously in equilibrium behaves when a disturbance is introduced. Consider a small disturbance introduced to the system at time td. If the system returns to its original (or closely related) state of equilibrium after being disturbed, the system is considered stable (Frisch, 1935; Sterman, 2000). If the small disturbance forces the system further away from equilibrium with the passage of time, the system is said to be in unstable equilibrium. These same definitions are useful in understanding the relationship between the CAS flocking metaphor and DEA/DPEM approach to productive efficiency.

2.3.2.3 Dynamic Technical and Allocative Efficiency Measurement

Vaneman and Triantis (2007) extends the notion of static technical efficiency to technical efficiency over time. The result is the dynamic efficiency plane as shown in Figure 2-9, below. This graph portrays two input axes x_1 and x_2, and a time axis t. In this graph the isoquants are increasing to the upper right. In a continuous time problem the level of output y is represented by an isoquantic plane. Likewise, the isocost lines are also represented in continuous time, and are depicted as the isocost plane. In a two-dimensional (or static) representation, overall productive efficiency is achieved at the points of tangency between the isoquants and isocost lines. In a continuous time environment this overall productive efficiency is achieved along a line where the isoquant and isocost planes are tangential. This line is known as the dynamic expansion line. The dynamic expansion line represents the most efficient (overall productive efficiency) path to traverse during a transient period $[t_0, t]$.

Figure 2-9. Dynamic Efficiency Plane (Vaneman and Triantis, 2007, p.85)



2.3.3 DEA Axioms of Production

Underlying DEA is the “theory of the firm” (Hendersen and Quandt, 1980). Included in this theory are the axioms of production, which concisely articulates the fundamental patterns of production. These axioms are building blocks of DEA. A CAS representation of efficiency should initially conform to the axioms or have a well-articulated purpose for relaxing the axiom. The axioms of production are:

- Axiom 1, (No Outputs) it must be possible for the system to produce zero outputs even when inputs are provided.
- Axiom 2, (No Free Lunch), outputs can never be produced in the absence of inputs.
- Axiom 3, (Free Disposability), it must always be possible to produce the same level of output even if the levels of input vary.
- Axiom 4, (Scarcity), the level of outputs that can be produced is limited or bounded. Finite inputs can only yield finite outputs.
- Axiom 5, (Closedness), it is possible to produce only positive real numbered amounts of outputs with only the positive real numbered amounts of input.
- Axiom 6, (Convexity) If a series of inputs x_i can produce y, then any weighted combination of x_i can produce y.

As stated above, the linear programing approach with its objective function and constraints embody concepts of productive efficiency that conform to basic physical laws and to known economic patterns of production. These patterns of are known in DEA as the “axioms of production.” For a representation of productive efficiency to be considered valid, it must conform to these axioms. Below is a brief introduction to the dynamic formulation of these axioms as recently defined by (Vaneman and Triantis, 2007).

The first production axiom is separated into two parts.

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

As a result of this axiom, the origin of a Cartesian coordinate scale must always be an element of the output or productivity space *P* for all elements of the input space.

Dynamic Axiom 1(a). $0_t \in P(x_{t-to}; y_{td-to}) , \forall\ (x_{t-to}; y_{t-to}) \in \Re^N_+,$

The spirit behind this axiom is that if no inputs are entered into the system during the time horizon [t_0, t_d], the system would come to or remain at rest or in a state of static equilibrium.

To conform to this axiom the CAS flocking metaphor would have to include the possibility of a DMU producing zero output or the productive efficiency being zero for an increment of time.

Axiom 1(b), the no free lunch axiom, further amplifies Axiom 1(a). This axiom is known as the “No Free Lunch” axiom (Färe and Primont, 1995, p. 27). It states that it is not possible to produce outputs [or stay at static equilibrium] at time t, in the absence of inputs during the time interval [t_0, t]. Axiom 1(b) is represented dynamically as:

Dynamic Axiom 1(*b*). $y_t \notin P(x_{t-to}; y_{td-to}) = 0$, if $y_t > 0$

The CAS flocking metaphor would have to confirm that during any time when inputs are 0 that no outputs are produced during that period.

Axiom 2(a), the weak input disposability axiom, which can also be thought of as the "little input slack" or "strong proportionality to changes in inputs" axiom, states that if all inputs are increased proportionally, outputs will not decrease. If inputs are not increased proportionally, outputs may decrease. (Färe and Grosskopf, 1996). The DPEM dynamic axiom further expands upon this concept because if inputs are increased proportionally during the time horizon $[t_0, t]$ then output will not decrease at the corresponding time t. However, if inputs are not increased proportionally during $[t_0, t]$, then outputs may decrease at the corresponding t. The dynamic weak input disposability axiom is represented as:

Dynamic Axiom 2(*a*)

$$\text{If } y_t \in P(x_{t-to}; y_{td-to}) \wedge \lambda \geq 1 \Rightarrow y_t \in P(\lambda x_{t-to}; y_{td-to})$$

When using the CAS flocking metaphor to simulate the productive efficiency of systems with weak input disposability it would be necessary to confirm that when all inputs are increased proportionally that outputs do not decrease.

Axiom 2(b), the strong input disposability which can also be thought of as "lots of input slack" or "weak proportionality to changes in inputs" axiom, states that if any input increases, whether proportional or not, output will not decrease (Färe and Grosskopf, 1996). In a dynamic environment, if the increases to x_{t-t0} during the time horizon $[t_0, t]$ are proportional or not, than the output y_t at the corresponding time period t will not be reduced.

Dynamic Axiom 2(b).

$$\text{If } y_t \in P(\breve{x}_{t-to}; y_{td-to}) \wedge x_{t-to} \geq \breve{x}_{t-to} \Rightarrow y_t \in P(x_{t-to}; y_{td-to})$$

When using the CAS flocking metaphor to simulate the productive efficiency of systems with strong input disposability it would be necessary to confirm that when inputs increase whether proportionally or not that outputs do not decrease.

The third production axiom is also separated into two parts.

Axiom 3(a), the weak output disposability which can also be thought of as “little output slack” or “strong proportionality to changes in outputs” axiom states that a proportional reduction of outputs is possible (Färe and Primont, 1995). Output slack can be thought of as waste or undesirable output. This axiom allows for a reduction in waste but requires that a proportional reduction in desired outputs occur as well. Thus if output y_t is produced by input x_{t-t0}, a weighted output □y_t can also be produced by input x_{t-t0}, when $\varphi y_t < y_t$. The dynamic weak output disposability axiom is represented as:

Dynamic Axiom 3(a).

$$y_t \in P(x_{t-to}; y_{td-to}) \wedge 0 \leq \varphi \leq 1 \Rightarrow \varphi y_t \in P(x_{t-to}; y_{td-to})$$

When using the CAS flocking metaphor to simulate the productive efficiency of systems with weak output disposability it would be necessary to confirm that when any outputs are reduced, all outputs, be they desirable or not, are reduced proportionally.

Axiom 3(b), the strong or free output disposability, which can also be thought of as the “lots of output slack” axiom, states that outputs can be disposed of without cost. The cause of this condition may be an inefficient production process that generates waste that can be discarded without consequences (e.g., smoke from a production process being emitted to the environment can be considered a costless disposal of an undesirable output in the absence of pollution regulations) (Färe and Grosskopf, 1996). In a dynamic system, production processes during the interval [t0, t] may yield outputs that are disposed of without costs, if and only if at least one output variable is exogenous to the system. Otherwise, they will create feedbacks into the system endogenously that will have performance consequences. Dynamic Axiom 3(b) is represented by:

Dynamic Axiom 3(b)

$$y_t \in P(x_{t-to}; y_{td-to}) \wedge \breve{y}_t \leq y_t \Rightarrow \breve{y}_t \in P(x_{t-to}; y_{td-to})$$

When using the CAS flocking metaphor to simulate the productive efficiency of systems with strong or free output disposability that changes in undesirable output be allowed to occur without adversely effecting overall productive efficiency.

Axiom 4, the scarcity axiom states that the output set is bounded in some manner. Thus finite amounts of input can only yield finite amounts of output (Färe and Primont, 1995). In a dynamic environment, the inputs are also bounded within the time domain. Thus bounded resources within [t_0, t] can only yield finite outputs at corresponding time t. Dynamic Axiom 4 is represented by:

Dynamic Axiom 4

$$\forall x_{t-to} \in \Re^N_+,\ y_t \in P(x_{t-to}; y_{td-to}) \text{ is a bounded set}$$

When using the CAS flocking metaphor an analyst would have to confirm that the set of possible outputs is bounded in some manner. When, for example, the end points of the efficient frontier do not include an x or y intercept the analyst can assume the horizontal or vertical line that includes these points.

Axiom 5, the closedness axiom, states the output set is not limitless, it is finite.

Färe and Primont (1995) state that if every sequence of output vectors y_j can be produced from inputs xi, then x can produce y. This assumes that the output set y is a series of vectors $y_j = (y_1, y_2, y_3, \ldots y_m)$ such that $\lim_{j\to\infty} y_j = y_j = y$. In the dynamical environment, if the inputs x at time $t\text{-}t_0$ can produce every sequence of vectors y_j at time t, then $x_{t\text{-}t0}$ can produce y_t. Dynamic Axiom 5 is shown as:

Dynamic Axiom 5.

$$\forall\, x_{t\text{-}to} \in \Re_{+}^{N},\; y_{\,t} \in P(x_{t\text{-}to};\, y_{t\text{-}to}) \text{ is a closed set}$$

The scarcity and closedness axioms ensure that the output space function $P(x)$ is a compact set, a finite set in space that contains all possible limit points.

In the CAS flocking metaphor, as long as the possible set of alignments, cohesions and separations is finite the CAS solution conforms to this axiom.

Axiom 6, the convexity axiom, states that a convex set is the resultant of a weighted combination of two extreme points. The weighted combination yields a line segment that joins the two points (Hillier and Lieberman, 1995). The extreme points and the line segment must all be contained in the solution space. Thus if x_i and $\breve{x}_i$ are both a series of inputs that can produce y, then any weighted combination of x_i and $\breve{x}_i$ can produce y. In a dynamic sense, x_i and $\breve{x}_i$ can be inputs during different times within the time interval $[t_0,\, t]$ as long as their respective outputs share a common time period t. DA.6 is described as:

Dynamic Axiom 6.

$$\forall\, x_{t\text{-}\,to} \in S(y_t) \in \Re_{+}^{N} \; if\; 0 \le \lambda \le 1 \Rightarrow \lambda\,(x_{t\text{-}to};y_{\,td\text{-}to})+(1\text{-}\,\lambda\,)(\breve{x}_{\,\tau-\tau 0};y_{\,td\text{-}to}) \in S(y_t)$$

In the CAS flocking metaphor all possible solutions alignment, cohesion and separation of the DMU in a period of time, must be contained within both the input and output spaces of the problem being analyzed. This can be confirmed mathematically by checking to see that the value of alignment, cohesion and separation functions are continuous and have value at their midpoint of every interval in its domain that do not exceed the arithmetic mean of its values at the ends of the interval.

2.4 Summary of DEA Building Blocks

In summary, the building blocks of DEA are the production possibility space, which encompasses the range of possible solutions, the decision-making unit that represents each member of the producing population, and the production or efficient frontier defined by a sub-set of the most efficient decision-making units. The building blocks of DEA also include the notions of technical, allocative and overall efficiency, which provide measures of comparison among the DMU population. Additionally, the building blocks of DEA include extensions of the static notions of DEA to incorporate changes in efficiency over time and an understanding of meaning of equilibrium and stability with respect to the analysis of productive efficiency over time.

3 Associative Inferences among the Building Blocks

3.1 Approach

The objective of this chapter is to propose a CAS-based approach for the analysis of the efficiency of management systems. For this research, management systems include any enterprise in which humans actively guide the key decisions of the enterprise. It is assumed for purposes of this paper that improving efficiency is a fundamental business practice and guides decision-making in the management system for the purpose of minimizing required resources and/or maximizing outputs. Management systems are treated as CAS ecosystems rather than cybernetic machines, recognizing the autonomous, goal-oriented, non-deterministic, non-linear nature of decision-making and recognizing the importance of the interactions among decision-makers in the lifecycle of a management system.

In this paper a conceptual bridge is established between CAS thinking as defined by Holland (1999) and the DEA form of efficiency analysis, as described by Cooper, Seiford, Tone (2007). Section 2.0, above, first identified and defines below, the key building blocks of CAS (environments, agents, goals, rules, percepts, actions, etc.) and the key building blocks of DEA (production possibility space, decision-making units, efficient frontier, inputs, outputs, etc.). This chapter asserts the inferences about the associations between and among them. A specific ecosystem metaphor is introduced, known as flocking, originally developed by Reynolds (1987), to explain the complex behaviors of self-organizing systems and introduce agent-based modeling (ABM) as a means of implementing and experimenting with these associations. Finally, a specific management system is introduced composed of the decision-making units of a population of deregulated electrical power plants, as a means of illustrating the nature and potential value of these associations. In (Dougherty, Ambler and Triantis, 2014b), and in Chapter 4 of this research, the constraint generating procedures (CGP) is explained, the NetLogo simulation platform and the modified NetLogo code required to implement these conceptual associations.

3.2 A Combined CAS ABM and DEA Form of Analysis

3.2.1 Associative Inferences

Having described, in the previous chapter, the essential building blocks of CAS ABM, the CAS flocking metaphor and the building blocks of the DEA form of productivity analysis relevant to this research, this chapter will now turn to associating them conceptually (i.e., a DEA DMU is associated conceptually in CAPEM with a CAS ABM agent) and making inferences about these associations (i.e., the CAS ABM agent can make essential policy decisions that would be made by a real-world entity represented in DEA as a DMU). In this section descriptions of the associative inferences made among the building blocks that form the complex adaptive approach to efficiency analysis that will be labeled in this research as the Complex Adaptive Productive Efficiency Model (CAPEM) are described. In a companion paper to this research (Dougherty, Ambler, Triantis (2014b) and in Chapter 4 below, the constrained generating procedures (CGP) and software implementations that make up the CAPEM capability are presented. Table 3-1 below summarizes the associative inferences. In the leftmost column listed are the primary building blocks of DEA. The column headings across the top of the table group are the building blocks of CAS. These headings are provided in two categories, individual decision-making and collective decision-making. The other two columns identify illustrative examples of each of these categories. Within the table cells CAS ABM concept that constitutes the associative inference is depicted.

Table 3-1. CAPEM Associative Inferences

Associative Inferences	Individual DecisionMaking	Individual Power Plant	Collective Behavior	Power Plant Management System
Decision-Making Unit (DMU)	ABM Agent	Individual Power Plant	ABM Environment	Population of Power Plants and the Corporate Market Place
Production Possibility Space (PPS)	ABM Agent Percept, Action and Communication	Location, Heading of Other Power Plants; State of the Corporate Market Place	Interaction among agents and with their environment	Corporate Market Place
Efficient Frontier (EF)	ABM Agent Goal, Individual Optimization	An Efficient Power Plant	Collective Optimization	Set of the Most Efficient Power Plants
Technical Efficiency (TE)	ABM Agent Location and Heading	Measure of Plant Technical Efficiency	ABM Movement, Change in Efficiency Over Time	Patterns of Collective Behavior (Emergence)
Production Function (PF)	Agent Internal Rules that conform to relationships among the Factors of Production	Relationships Between Fuel, Labor, Energy and Electrical Production	Input Minimization/ Output Maximization	Minimization of the Use of Fuel and Labor
Axioms of Production	Agent Internal Rules that conform to real-world laws of physics and behavior	No Free Lunch, No Activity, Free Disposability	Corporate behaviors conform to real-world laws of physics and behavior	Convexity, Boundedness
Policy Choices	Agent Internal Rules Flocking - Alignment and Separation	Risk Avoidance, Self-Preservation	Hedging, Collaboration	Alignment and Separation Among Power Plants
	Agent Internal Rules Flocking – Cohesion	Mimicry	Best Practices Decision-Making	Cohesion Among Power Plants
Capabilities/ Adaptations	Agent Internal Rules - Maximum Turns, Minimum Distances	Capability, Limitations on Change per Increment of Time	Collective Effect of Individual Capabilities and Limitations	Collective Change Throughout a Period of Performance
Patterns of Behavior	Changes in DMU TE over time	Stability of Individual Power Plant TE's over Time	Changes in Population TE over time	Change in Time required for the population of ABM Agents to reach the DEA EF

It is the intent here to introduce, through these associative inferences, the conceptual basis for this research. A simple management system made up of a collection of component decision-makers and their operating environment is assumed. For illustrative purposes, a data set collected on a population of 82 deregulated power plants by Rungsuriyawiboon and Stefanou (2003) is used and is presented in Chapter 5 below. This population is treated as a single management system or corporation call in this research, PowerCorp.

3.2.2 Individual Component Decision-Making in CAPEM

3.2.2.1 The CAS ABM Agent and the DEA Decision Making Unit

Column 1, Row 1 of Table 3-1 above, associates the CAS ABM agent with the DEA DMU and infers that the CAS ABM agent can, for purposes of this research, adequately represent relevant characteristics and behaviors of individual components of a management system. For this research the term “agent DMU” (ADMU) is coined to represent this association. Intuitively, it is understood that for an ADMU to make a decision, a decision-maker must have a goal and either implicit or explicit rules that guide these decisions.

Representing individual management system decision-makers as individual ADMUs, offers the opportunity to incorporate into the analyses a very large number of like system decision-makers or alternatively a wide range of unique decision-making units each with its own goals, rules, perceptions and actions (Miller and Page, 2007). As semi-open entities, ADMUs meet the DEA requirement for independence among DMUs. A single power plant for example pursues its own internal goals and adheres only to its own internal rules. It accepts selected pieces of information, like the current state of other power plants, but it is not necessarily driven by the goals or rules of its parent corporation or the goals or rules of other power plants. It is semi-open and autonomous. In other words, its behaviors result only from its own choices about how to react/behave, based on its own goals and rules and to the information it receives from outside itself (Holland, 1999).

This association can become increasingly more sophisticated as the representation of a decision making unit and its larger management system context is analyzed at greater and greater levels of detail. Consistent with the principles of CAS thinking, the management system decision-makers represented by the ADMUs can be defined at ever increasing levels of granularity as long as at any level of granularity, the rules that govern them and the nature of the interactions among ADMUs continues to be simple and tractable (Holland, 1999). It is this similarity between the human-like ABM agent with its goals, rules, percepts, actions and the analogous characteristics of a management system decision-maker that underpins this analysis. These concepts are expanded on below.

3.2.2.2 Individual Goals

An individual component decision-maker within a larger management system may have a wide range of desired outcomes or goals. Columns 1 and 2 of Row 4 associate CAS ABM agent goals with the maximization of output or minimization of inputs inherent in a DEA DMU and infer that this association is representative the desired goals of individual components of a management system. One such goal, for example, may be a desire for continuous improvement of productive efficiency in terms possibly, of technical efficiency, cost efficiency or overall efficiency. The goal or frontier of a DMU is expressed in terms of the DEA production function that is, the optimum possible production based on a properly weighted set of inputs (Cooper, Seiford, Tone, 2007). Goals of an individual CAS ABM agent are explicit and are implemented in the form of the ABM language being used (Gilbert, 2008).

In this research, consistent with the DEA methodology, each ADMU seeks continuous improvement and ultimately optimum technical efficiency with respect to all other ADMUs. Whether the goal is longer-term system-wide optimization or nearer-term improvement, CAS ABM computing language semantics and syntax combined with the DEA formulations provides a clear, concise, yet rich means for expressing these goals.

3.2.2.3 Individual Rules

Decision-makers in any particular management system typically employ what are known as business rules (Jeston and Nelis, 2008). Business rules embody the collective intelligence and wisdom of the business area and are used with more or less discipline depending most often on the personal discipline of the decision-makers themselves. Column 1, Row 5 associates CAS ABM agent rules and the DEA production transformation function and infers that they appropriately represent the concept of corporate business rules. Individual decision-makers, such as individual power plants who are also members of in a larger corporate body of power plants and who have individually and corporately accepted the policy of collective action may under certain circumstance, better achieve their individual goals by sharing a common set of business rules.

In this research the specific rules of this industry are replaced with the rules of flocking, alignment, cohesion and separation (Reynolds, 1987). They are implemented explicitly in the CAS ABM NetLogo (Wilensky, 1999). In this model it is assumed that the aggregate business rules of members of a management system can be represented by these three rules of flocking and that all members of the systems can achieve consensus or alignment with respect to the general strategic direction of the system as a whole. CAPEM offers the potential of gaining insights into value of cohesion of individual DMUs with the most efficient members of the larger management system. Finally, CAPEM offers decision-makers the potential of gaining insight into the value of avoiding direct competition with other members of the management system as represented by the flocking rules for separation.

3.2.2.4 Individual Percepts

Column 1, Row 5, associates the CAS ABM percepts and inputs of a DEA DMU and infers that this association is representative of the factors of production in a management system. An individual component decision-maker within a larger management system may have a wide range of factors that it can sense or perceive. Individual decision-makers, for example, often have a massive array of available information but are able to understand and actually utilize only a small sub-set of this information. This information may include information on the state of needed resources such as labor, fuel or energy. This information may include the state of neighboring components in terms say of their current technical efficiency. In DEA analyses a DMU has information only about its own factors of production (Cooper, Seiford, Tone, 2007). Typically, there is no concept in DEA of DMUs directly sharing information. In contrast, percepts of individual CAS ABM agents may include information on every variable defined within the CAS ABM environment or may intentionally select a sub-set of available information depending on the design of the simulated experiment. In the power plant example of Chapter 5 the percepts of an individual power plant perceives the positions of all other power plants in the CAS ABM agent environment. For experimentation purposes this selection could be modified to a sub-set of other power plants within a specified region of the production possibility set, for example, influencing the set of power plants with which it would interact.

3.2.2.5 Individual Actions

Row 2, Columns 1 and 2, associates an individual decision-maker within a larger management system which may or may not affect other individual decision-makers of the large management system. A single decision-maker may or not affect the management system as a whole. Actions taken by one ADMU to increase its labor force, for example, may or may not affect the ability of another ADMU to acquire labor. In the standard DEA approach there is no explicit notion of one DMU acting on another. In the power plant example, it may translate into using more labor, for example, to reduce the level of energy required to produce the same level of electrical power. In this research ADMUs report the current position in the production possibility space to the ABM environment and other ADMUs may or may not choose to perceive or be affected by this information. Generally, in CAPEM all inefficient ADMUs perceive the state of all other inefficient ADMUs in each period of time. They also perceive and are therefore affected by the state of the two nearest efficient ADMUs from the peer set. These are the only percepts and actions that are necessary in CAPEM to lay the foundation for flocking.

3.2.3 Collective Management System Decision-Making in CAPEM

3.2.3.1 Collective Goals

Gaining insights into individual decision-maker choices over time as described above can only be of value when understood in the context the collective complex adaptive behaviors being exhibited by the system as a whole (Holland, 1995). Gaining insights into this collective and emergent behavior of the system is as important, potentially even more important, to some decision-makers, than the choices being made by individual decision-makers (Craig and Harris, 1973). Row 3, Columns 3 and 4 associate the DEA efficient frontier with collective goals. For purposes of this research management systems could choose one of two primary collective goals with respect to production efficiency. Consistent with DEA methods, management systems seek, as a collective system, to either maximize outputs for a given set of inputs or minimize inputs to produce outputs (Cooper, Seiford and Tone, 2007).

3.2.3.2 Collective Rules

Row 5, Columns 3 and 4 associate the DEA production function with the collective goal (input minimization, or output maximization). Row 6, Columns 3and 4 associates the DEA axioms of production with collective rules. Consistent with the theory of the firm described previously (Hendersen and Quandt, 1980), management systems adhere to a set of axioms of production (Cooper, Seiford and Tone, 2007). From a CAS ABM perspective, these axioms constitute the collective system rules, which both enable and constrain the system as a whole. In CAPEM great lengths have been taken to ensure that the CAS ABM environment fully implements and adheres to these axioms of production. A more complete description of the implementation of the axioms in CAPEM is provided in Section 4.6 below.

3.2.3.3 Collective Percepts and Actions

Within the scope of this research there are no collective percepts or actions. Real world management systems may collectively perceive aspects of their larger environment and generally accept exogenous inputs as if they were an open system. Similarly real world management systems generate outputs and act on their environment but recall that this exploratory research focuses exclusively on collective behaviors driven solely by decisions made at the individual level. Row 2, Columns 3 and 4 of the chart associate collective percepts and actions with the DEA PPS. For purposes of this research and generally speaking, CAS ABM environments are implemented as fully closed systems and therefore preclude percepts, exogenous inputs or outputs and precludes acting or affecting anything outside the closed CAS ABM environment. Any variable that is necessary for the analysis must therefore be incorporated into the CAS ABM environment. This represents the challenge of having the appropriate ABM and DEA variables specified in this representation. The CAS ABM simulation fully enforces the closed environment paradigm. All factors of production are represented within the CAS ABM environment. This representation adds a different perspective on the impact of contextual variables in efficiency analysis since the analyst could experiment with different input/output specifications as well as different combinations of contextual variables to explore potentially important underlying theoretical constructs and relationships.

Analysis of the environment beyond the management system itself can be accomplished in a CAS ABM paradigm but would require hierarchical aggregation and a change in the granularity of the analysis (Holland, 1995). To perform this kind of analysis would require treating the collective management system as a single agent or an autonomous cluster of agents, in a larger CAS ABM environment. The value and means of doing so are beyond the scope of this research. However, the approach potentially offers an alternative view of the scaling issue, i.e., going from individual firms to industry and sectors of the economy. Alternatively, one could explore the possibility of going from the firm to specific production processes within the firm.

3.2.3.4 Collective Interactions, Feedback and Discovering Emergence

Row 2, columns 3 and 4 associates directly the interactions in CAPEM between the ADMUs and the CAS ABM environment and the interactions between individual decision-makers and the management system environment. An individual decision-maker's awareness of collective system factors such as standing corporate policies or availability resources is represented in this manner. From the CAS ABM environment an agent is able to sense the global variables such as the physical limits of the environment, distance and time horizons of the system as a whole. Distance in this case translates to change in use of the factors of production (i.e., fuel and labor). The time horizon is specific to a study scenario as well and must conform to the purpose of the study, be it measured in days, weeks, months or years, etc.. Agents interacting with their environment are able to affect the state of the values of input resources and the output products that are defined as global variables (Wilensky, 1999). Both individual and collective decision-making is of course affected by awareness of the state of these global variables.

In a CAS ABM form of analysis feedback is represented by awareness of the change of states of other agents and the elements of the CAS ABM environment (Holland, 1995). Such a representation provides a means of defining feedback at a very granular level among a nearly unlimited number of explicitly represented system components. In the corporate power plant example, interactions among CAPEM ADMUs (individual plants) and between each ADMU and its CAPEM environment provide continuous feedback over time. Individual power plants sense and acquire as much or as little information as desired or allowed by its neighboring power plants, each adhering to their own rules for sensing (percepts), responding and sharing information. Feedback is also provided to each power plant from the larger corporation, the CAS ABM environment, sharing corporate level information as updated global variables (i.e., the DEA Efficient Frontier) in the simulation. Individual power plants also act on other power plants and the corporation as a whole by reporting their own latest position in the production possibility space that has changed as a result of their own recent, internal decisions. These interactions and the behaviors that result from this detailed continuous feedback processes are the source of the collective behavior of the system and potentially lead to emergent system behaviors. Implemented appropriately this capability enables the analyst to investigate the difference between behaviors that are directly traceable to individual goals and rules and patterns of overall collective behavior that might, if intentionally repeated, lead more often than not to successful outcomes.

3.2.3.5 CAS Agent Goals, the Transformation/Production Process and the Efficient Frontier

The next associative inferences are made between individual decision-maker goals represented as CAS ABM agent goals, the underlying transformation function and the efficient frontier. Rows 3 and 5, Columns 1 and 2 associate individual CAS agent goals with the DEA efficient frontier (Row 3) and with the DEA production function (Row 5). The goal of any management system with respect to productive efficiency is to constantly improve and ultimately to either produce the maximum conceivable outputs for the available inputs (output-maximization) or minimize to the greatest possible degree, the inputs required for producing a given level of outputs (input-minimization). One of the fundamental challenges for a management system is to know what is possible given the underlying technology (Gilbert, 2008).

In DEA, the benchmark of what is possible is driven by the specification of the mapping between the inputs and the outputs (production process representation of the technology) and the position of the frontier. DEA DMUs know what is possible by checking with all other similar DMUs and determining which ones are most efficient. The subset of DMUs that either maximize outputs or minimize inputs relative to the other DMU in the set, are deemed the benchmark. When the productive efficiencies of all DMU (in terms of inputs, outputs or ratios) are normalized and plotted on a coordinate scale the most efficient DMU form a piecewise linear curve called the efficient frontier. The efficient frontier is the benchmark or goal that all other DMU seek to achieve. Inefficient agent DMUs make modifications, in whatever ways are available to them, to become as efficient as those on the efficient frontier, the benchmark of efficiency. Reaching the efficient frontier is the goal of each agent DMU.

The amounts of labor, capital, energy required to produce electric power, for example, are subject to the laws of physics. No amount of power plant labor, for example, can replace any amount of fuel required to produce electricity. A certain labor force is however needed to run the plant and properly utilize fuel and energy. The estimation of the frontier can be computed using DEA or estimated using econometric methods (Kopp, 1981). Once computed or estimated the production function/frontier can be used repeatedly to determine the optimum possible solution for a population of power plants under any given set of circumstances. A simplifying and intentionally limiting assumption in this research is that the efficient frontier does not change over time.

Driven by polices based on the rules of flocking inefficient agent DMUs seek to adjust the individual use of inputs and or the production of outputs in an effort to attain the goal represented by the efficient frontier (Cooper, Seiford and Tone, 2007). The efficient frontier then represents the ultimate goal of each DMU and the collective goal of the system of decision-makers.

The initial implementation of the CAS ABM defines the DEA efficient frontier graphically (Dougherty, Ambler, Triantis, Part (2014b) and Chapter 4 below. The most efficient DMUs are those that are at the extreme outer edge with respect to the origin for an output maximization problem and the extreme inner edge for the input minimization problem. The piecewise linear curve formed by joining the positions of the most efficient DMUs constitute the efficient frontier. Using the efficient frontier as the benchmark or goal, all DMUs not on the efficient frontier make choices in terms of whatever options are available to them to change the usage of inputs and the production of outputs in an attempt to be become more technically efficient.

3.2.4 The CAS ABM Environment, the DEA Production Possibility Space and Productive Efficiency

3.2.4.1 The CAS ABM Environment and the DEA Production Possibility Space

In this research, the DEA production possibility space (PPS) is the DEA representation of the management system environment (Cooper, Seiford and Tone, 2007). In CAPEM, the CAS ABM environment is the CAS representation of the DEA PPS and is fully capable of incorporating all the factors needed to support individual and collective decision-making. CAPEM has implemented the CAS ABM environment in NetLogo (Dougherty, Ambler, Triantis, 2014b) and Chapter 4 below.

The CAS ABM environment is a closed system that enables the analyst to create dynamic, non-linear representation of changes of productive efficiency. Each axis typically represents one of the factors of production. In the CAPEM CAS ABM environment the analyst can embed real world units of time and distance. For example, in the power plant example each increment of time in the simulation can represent one month and each cell in the simulation environment geometry can represent units of measure for each of the three input resources i.e., a BTU for fuel, a dollar of capital and a person month of labor. Coordinate values (ADMU locations) in the simulation environment correspond to a point in the production possibility set. Differences in coordinate values (locations) represent the relative differences in the consumption of resources and the production of outputs and consequently one can interpret these as differences in the technical efficiency of power plants. Differences in technical efficiency can be measured in the simulation environment as both a distance between power plants and a difference in the direction of movement.

Changes in distance over time or the velocity an ADMU represents the speed with which a power plant is changing its technical efficiency. The rate of change of the velocity of movement of a power plant in the simulation translates to acceleration or deceleration in the change of technical efficiency of the power plant over time.

The heading (velocity and direction) of a CAS ABM agent in any increment of time then represents an individual decision-makers choice of the level of inputs for the next increment of time (month). This is in effect the production policy choice for that agent. Acceleration and deceleration depict patterns of change in agent production policies over time.

3.2.4.2 CAS ABM Environment and DEA Productive Efficiency

3.2.4.2.1 Measuring Productive Efficiency

Row 2, Columns 1 through 4, associate the CAS ABM environment with both individual and collective productive efficiency. DEA output maximization and input minimization approaches establish the context for measuring the relative productive efficiency across the reference set of DMUs (Cooper, Seiford and Tone, 2007). The coordinates of the individual DMUs in the PPS provide us with a means of detailed graphical measurement and analysis. Were it physically possible an individual inefficient DMU once informed of the exact distance and direction would set a course straight to the efficient frontier. The most efficient path in a flat landscape with no other constraints would of course be the shortest line between the point and the nearest point on the efficient frontier. Measuring the distance of this straight line path might be a useful measure of efficiency. Unfortunately this measure provides only a part of what is needed and is only relevant to the DMU itself. To establish a common means of measuring efficiency across a whole population of DMUs DEA requires a common point of reference. DEA offers a number of ways to measure direction and distance. For purposes of this research the measurement of the radial line from the origin, through the DMU's current location in the efficiency space, to a point on the efficient frontier (Cooper, Seiford and Tone, 2007) has been employed. In Figures 2-4 and 2-5 above and replicated here as Figures 3-1a and 3-1b, for the convenience of the reader, this line is represented as the line OC'.

Figure 3-1a. The Building Blocks of Standard DEA

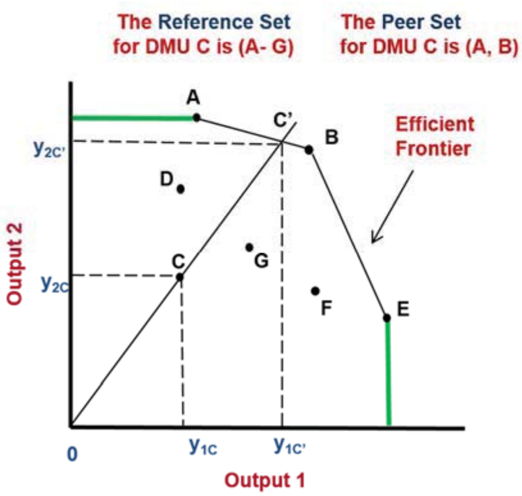
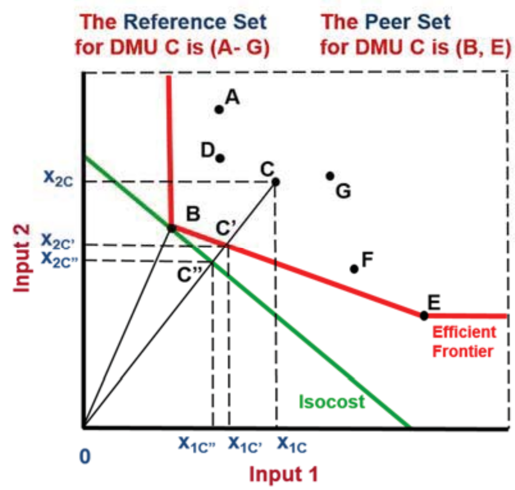


Figure 3-1b. DEA Building Blocks of Technical and Allocative Efficiency



CAPEM uses this same convention in the CAS ABM simulation to provide, at each increment of time, measurements of distances and direction that can be used to define efficiency. In the current version of CAPEM the EF is represented as an unchanging or static goal. In the future, the EF may also be represented as changing over time.

3.2.4.2.2 Technical Efficiency

Row 4 of the chart associates DEA technical efficiency with the individual and collective CAS ABM decision-making. Having established a common convention for measuring distance and direction a management system can chose a convention for measuring the various forms of efficiency. This research employs the DEA definition of technical efficiency (Cooper, Seiford and Tone, 2007). Defined originally by Farrell (1957) and implement the DEA definitions have been implemented in the CAS ABM code. The DEA definition of technical efficiency measures uses the factors of production, that is, the inputs and outputs of the system without regard to cost (Cooper, Seiford and Tone, 2007). In CAPEM an analyst can compare the current levels of inputs or outputs with the levels of inputs or outputs that would be optimal for that DMU. As described above technical efficiency is represented in Figure 2-6a (Output Maximization Policy) by the lines 0F and 0F’, TE = 0F/0F’. In Figure 2-6b (Input Minimization Policy) TE = 0H/0H’. Both figures are replicated here as Figure 3-2a and 3-2b respectively, for the convenience of the reader.

Figure 3-2a. Standard DEA Output Maximization

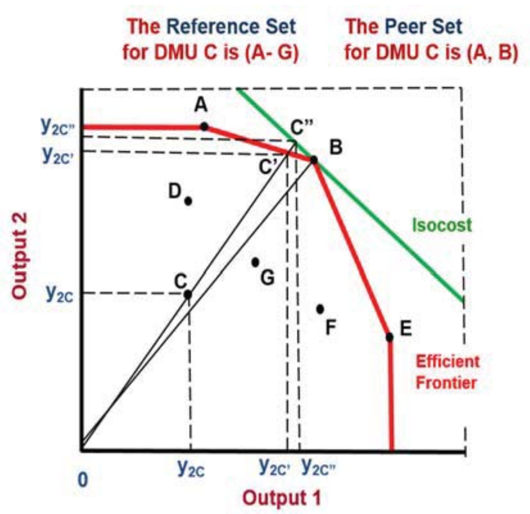
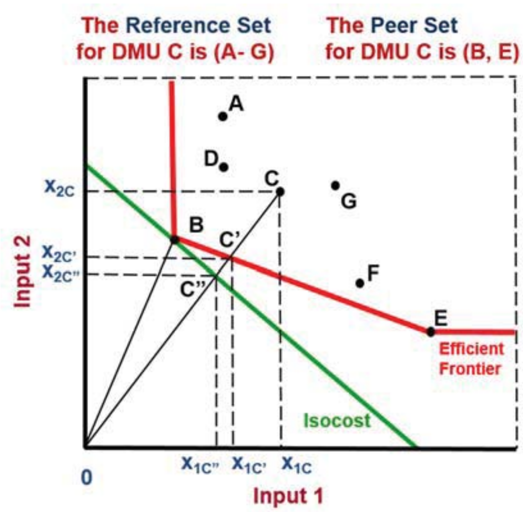


Figure 3-2b. Standard DEA Input Minimization



3.2.5 The CAS Agent Rules of Flocking and Management System Policy

Row 8, Columns 1-4, associate all the flocking factors included in the flocking metaphor with individual agent and collective management behavior. Management system policy is intended to guide individual system component decision-making (Gilbert, 2008). As previously stated management system policies or business rules are treated in this research as CAS ABM agent rules. CAS ABM agent rules used in this research are the flocking metaphor rules of alignment, cohesion, and separation and are implemented in the CAS ABM environment modified to embody a dynamic form of DEA productive efficiency (see Section 3.3). By implementing these common management system rules in a DEA defined CAS ABM environment CAPEM enables the decision-maker and analyst to experiment and capture information on rates of change over time and information on the states of the system decision-makers in terms of the level of inputs, outputs and technical efficiencies over time.

3.2.5.1 The CAS Alignment Metaphor and Management System Risk Avoidance

Row 8, Columns 1-4, associate alignment along with the other flocking factors included in the flocking metaphor with individual agent and collective management behavior. The ecosystem pattern of alignment behaviors postulates that the goal of the flock is to provide protection for its members against intrusion by a prey (Reynolds, 1987). By aligning with one another the flock creates the image of a much larger animal thus deterring prey from attacking. The ecosystem pattern of the use of alignment behaviors to achieve collective protection is employed to represent a common management systems behavior of collective risk avoidance (Kaplan and Norton, 2004). In the CAPEM implementation, rules of alignment represent the choices made by organizational decision-makers to follow the general "direction" set by members of their industrial sector or corporate organization. Competitive organizations are incentivized to choose such an approach or policy when they have confidence that over time they believe it will be most profitable to follow the current general direction of the larger system, industry or industrial sector. Like the protection provided to flock mates against natural prey by aligning with their flockmates, members of a management system or industrial sector can gain protection by aligning with other members of their management system by, for example, mimicking new products offered by others or adding features to a product line similar to those of others in the management system. This affords protection from being out of step with the market. Attack by prey in an ecosystem translates into many forms of organizational intrusions such as such as technology insertions; managerial decisions; implementation of efficiency improvement strategies such as process redesign, improved measurement tools; environmental changes; corporate raiding and mergers, etc.

Included also in the CAPEM implementation of the flocking metaphor is the NetLogo concept of a maximum alignment turn capability, as one system component seeks to move to align with the others. This introduces a concept very akin to the CAS concept of adaptability or learning (Johnson, 2001) and is very realistic in terms of the actual physical capabilities of a system component. It would be unrealistic to expect a physical system or even a decision-maker to always be free to change immediately in any way that is needed. A physical system would be constrained by the ability of the plant, for example, to modify plant layouts or modify resource inputs without at least a small time delay. CAPEM has retained this NetLogo feature and employs it to offer a decision-maker added fidelity of the representation and added insights resulting from the analysis.

3.2.5.2 The CAS Cohesion Metaphor and Management System's Best Practices

Row 8, Columns 1 through 4, associate cohesion along with the other flocking factors included in the flocking metaphor with individual agent and collective management behavior. To understand the ecosystem pattern of cohesion it is first necessary to understand that in a flock none of the members of the flock is actually a “leader” or exerts and form of control, in any way, over the decisions of another. Extensive study has determined that even the member of a flock that is out in front of the others just happens to be the one that is initially at one extreme or other of the flock (Reynolds, 1987). Flockmates may, for a time, cohere to the member of the flock at the extreme of the formation as a function of following their own internal rules but do not do so as the result of any form of control of one over another. The member of the flock who is initially at the extreme end of the flock is simply following its own internal rules. For this research an association is inferred between this behavior and the behavior of decision-makers in a management system. In CAPEM, inefficient ADMUs looking for the protection offered by the larger system chose to cohere to the most efficient members of the system. In the DEA paradigm these are the members of the system that form the benchmark for technical efficiency, those on the extreme edge of the production possibility set those previous described as forming the efficient frontier (Cooper, Seiford and Tone, 2007).

Smaller groups within the flock are formed when sub-sets of the flock cohere to different flock mates who are at the extreme edge of its awareness (Reynolds, 1987). These smaller groups, over a longer period of time converge to form a single larger flock. This behavior emerges not because of any control by the agents at the edge of the formation but because of their own desire for protection that translate to a choice they make to cohere to those that are most efficient. The most efficient power plants, for example, have no direct control over the others but in conformance with their internal rules individual power plants chose to cohere with the power plants whose choice of proportion of inputs or outputs have proven most efficient. The choices made by the most efficient ADMUs become de-facto corporate best practices. The most efficient power plants for example, do not exert control over less efficient power plants. The population of power plants, like the flocking agents are a leaderless band whose individual rules cause each member to cohere to whatever other power plant is at the extreme of the system of power plants. Power plants whose choice of certain proportions of fuel, labor or energy resulted in higher TE become the ones to which other less efficient power plants would seek to cohere.

The policies being followed by the most efficient power plants at the time of the analysis would, hypothetically, constitute a candidate best practice for others to mimic or emulate.

Included also in the CAPEM implementation of the flocking metaphor is the flocking concept of a maximum cohesion turn capability as one system component seeks to move to cohere with the most efficient system components (Wilensky, 1999). As with the maximum alignment turn, this introduces a concept very akin to the CAS concept of adaptability or learning and is very realistic in terms of the actual physical capabilities of a system component to modify its behaviors. It would be unrealistic to expect a physical system or even a decision-maker to always be free to change in any way what is needed, in every situation, in any period of time. A physical system would be constrained from cohering by the ability of a power plant, for example, to modify plant layouts to adopt the system best practice or modify resources inputs without at least a small time delay to those used by the most efficient components of the management system. CAPEM has retained this flocking concept and employs it to offer a decision-maker added fidelity of the representation of cohesion and added insights resulting from the analysis.

3.2.5.3 The CAS Separation Metaphor and Internal Management System Competition

In an ecosystem the need and means for this separation is obvious, physical collision would cause injury to the animal. For non-physical, abstract concepts such as efficiency it may be more challenging to find a proper or direct analog. The biological analogy for separation recognizes an animal's natural instinct to avoid collision and its instinctive response to taking a heading that for the longest possible time will enable it avoid another collision (Reynolds, 1987). Row 8, Columns 1-4 associates this concept with the management system concept of adhering to a corporate-wide shared approach that recognizes the value of maintaining a diversity of solutions or TE across the system (Kaplan and Norton, 2004). In a situation where, for example, resources available to the system as a whole are limited the need to achieve the greatest value to the system may result in the requirement for a suboptimal decision at the individual component level. A power plant, as noted earlier, may have to share scarce resources with other power plants, which may preclude the possibility of achieving identical technical efficiencies. The concept of separation may also translate to acknowledgement by the system of the uniqueness of the ADMUs in terms of their environments.

In terms of technical efficiency the inference is that no two power plants could ever use the same amount of inputs or outputs because of their uniqueness in such things labor demographics or age of equipment driving varying efficiencies in their use of energy or fuel or situational factors such as varying cost for transportation of resources. For purposes of this exploratory research the concept of separation of all such characteristics that make one system component unique from others, whether they translate directly or indirectly to the operational definition of technical efficiency used in this research.

Inferred also in the CAPEM implementation of the flocking metaphor for separation are associations with two other flocking concepts, minimum turn away and maximum separation distance. The first is analogous alignment and separation turns and represents the ability of one component to avoid making a decision that brings it directly into a competitive situation with another. The ability of two components to avoid competition for the same labor market in nearby regional areas would be an example of this kind of decision. If the availability of skilled labor in a region changes, it make take time for neighboring system components to adjust their hiring practices to avoid direct competition. The ability of component decision-makers to avoid competition for a common fuel source (causing higher overall fuel cost across the corporation) could be limited by the corporation's ability to change their approach to for example, resource transportation. They could, for example, choose rail transportation over road transport for whatever reason unique to the scenario.

The second flocking separation concept with respect to adaptability or leaning is separation distance. This concept enables decision makers to consider how much or how little separation is needed to avoid adverse consequences. How much variation, for example, in the size of the labor forces among power plants should be tolerated before the corporation feels the need to step in and impose a change on one or another power plant? Zero separation distance would require uniformity across the corporation. Larger separation distances infer greater flexibility in making choices related to avoiding adverse consequences. Once again, CAPEM has retained this flocking concept and employs it to offer a decision-maker added fidelity of the representation of separation and added insights resulting from the analysis.

3.2.6 CAS Agent Rules and the DEA Axioms of Production

As described above DEA methods of analysis are based on a set of axioms of production that anchor it firmly to the theories of actual production system behaviors (Vaneman and Triantis, 2003). Row 6, Columns 1-4 associate these axioms with an essential set of rules that must be enforced either by construction of the CAS ABM simulated environment that represents the PPS or as a rule implemented within individual ADMUs or both.

Adherence to axiom 1, the no activity axiom ensures that in CAPEM it is always possible to produce no outputs. This axiom 1 implemented simply by having (0,0) as the origin of the coordinate scale for the CAPEM PPS in the CAS ABM environment for the output oriented scenario. A power plant under most circumstances would not pursue a policy of producing no outputs. If however, a surplus of power drove prices below what was economically desirable a power plant might shut down and do just that. In CAPEM, a power plant pursuing such a policy for any increment of time would move in the direction of the origin (0,0).

Axiom 2, the no free lunch axiom ensures that CAPEM never permits the production of outputs without some level of input. Axiom 2 is implemented in CAPEM simply by defining the dimensions of the PPS, the vertical and horizontal axes, as the factors of production that are the inputs and or outputs of the DEA defined production possibility set. CAPEM allows a power plant, for example, to pursue a policy where the level of input for any particular resource is zero. The location of such a power plant in the CAPEM PPS would be on one of the axes. An error would be indicated by the CAS ABM simulation, if during a simulation a power plant with no input were to show a positive output value.

Axiom 3, the disposability axiom ensures that systems with the ability to vary the proportions of inputs and outputs are appropriately represented in the model. For a system component to varying the proportions of inputs and outputs it must first, be physically possible and second, it must be possible to dispose one or more of these inputs or outputs without prohibitive cost or without other consequences that would make the change either physically impossible or economically imprudent. In the efficiency literature disposability can be represented as weak or strong for both the input/output orientations. It is assumed that ADMUs exhibit free disposability representing the case where an ADMU is free to move freely throughout the PPS. Imposing other forms of disposability is beyond the scope of this research. Care has been taken in the conceptual design of CAPEM to do nothing that would limit or prevent the management system from considering the effects of or implementing other forms of disposability in the future.

A power plant, for example, that, for one reason or another, has access to excessive amounts of fuel at no extra cost (high disposability of fuel) can be undisciplined or wasteful in its use of fuel and still produce an expected amount of output (power). Its inefficiency due to lack of fuel discipline has no consequences. If however this power plant has little access to a skilled labor force wages would be higher. Lack of discipline in the use of labor has significant consequences (weak disposability of labor). In the first situation the power plant is free to pursue production policies that do not consider fuel costs or consequences. In the second situation it is less free to do so. DEA and the CAPEM simulation permits both scenarios to be represented as well as other scenarios that reduce or increase all inputs or outputs in the same proportion.

Axiom 4, the scarcity axiom, ensures that the range of possible outputs is bounded, that is, finite amounts of input can only yield finite amounts of output. The scarcity axiom is implemented in CAPEM by defining the CAS ABM environment in terms of real numbers only and by requiring any calculation for outputs used in the model to fall within the bounds of the CAS ABM environment that represents the PPS. Resources available for producing electrical power are finite, both physically real and limited in amount. Regardless of the combination of resources being used in the real world a power plant cannot produce unlimited amounts of power. CAPEM enforces this axiom and monitors results of the simulations to detect calculations that violate this rule. A power plant can only produce the amount of power it has resources to produce. In all cases resources are represented by real numbers.

Axiom 5, the closedness axiom, ensures that the range of possible outputs is a compact set, that is, a finite set in the CAS ABM environment that contains all possible limit points, including the origin, the horizontal and vertical intercepts, and the extremes of the PPS in the both the input and output orientations. This axiom is implemented in CAPEM in two ways, one for each of the primary modes of DEA analysis. For the output orientation mode, closedness is enforced by bounding the PPS with a line segment from the efficient ADMU with the greatest horizontal axis value, upward, away from the origin, to the nearest point on the horizontal axis and also by bounding the PPS with a line segment from the efficient ADMU with the greatest vertical axis value, over to the nearest point on the vertical axis creating a PPS that has a closed output orientation. As a result no single point in the PPS or on the portions of the boundary of the PPS that is defined by the horizontal and vertical axes is left undefined. For the input orientation closedness is enforced by bounding the PPS with a line segment from the efficient ADMU with the greatest horizontal axis value, outward, away from the origin, to the nearest point on the edge of the agent environment and also by bounding the PPS with a line segment from the efficient ADMU with the greatest vertical value, upward and outward, away from the origin, to the nearest point on the edge of the agent environment. Doing so creates a PPS that is closed for the input orientation. Again, as a result no single point in the PPS or on the outer limits of the agent enviroment.is left undefined. Any point beyond these boundaries is undefined either conceptually or in the real-world.

Axiom 6, the convexity axiom, is considered in CAPEM by this method used in this research to identify and display the DEA efficient frontier graphically. A convex combination of ADMUs is considered to be part of the frontier. On the frontier weighted combination of two extreme points yields a line segment that joins the two points. CAPEM enforces this relationship and monitors for calculations that that violate this rule. However, it should be noted that convexity is not assumed or enforced as ADMUS change their positions when adhering to the rules of alignment, cohesion, and separation.

3.3 Insights to be Gained from the Use of CAPEM

3.3.1 Detecting Expected Behaviors in CAPEM

By representing management systems as a collection of semi-open, independent system components in a closed CAS ABM system environment and by representing their dynamic decision making behavior as a CAS metaphor produces a range of valuable insights across a wide range of subject domains and conditions. In the more narrowed scope of this research, the premise is that improvements in the management system productive efficiency resulting from adoption of the validated ecosystem metaphor of flocking (Wilensky, 1999) can be measured. More explicitly the premise is that by adopting flocking as corporate strategy and adhering to the rules of alignment, cohesion, separation inherent to the flocking metaphor decisionmakers can make a series of complex individual and collective decisions that result in continuous collective improvement of efficiency over time.

Making the associative inferences described above makes possible the development of a new analytic capability that overcomes a number of former analytic constraints and extends DEA productivity analysis into the realm of complexity science. This capability then enables insights into three narrowly focused aspects of management system behaviors which are expressed as the following premises: 1) Increased adaptability to each of the flocking factors by individual component members of the management system result in reduced time required to achieve maximum possible system-wide technical efficiency; 2) Increased adaptability to each of the flocking factors by individual members of the of the system increases the maximum achievable system-wide technical efficiency; 3) Increased adaptability to various combinations of the flocking factors by individual component members of the management system result in increases in the achievable collective level of technical efficiency and in reduced time required to collectively achieve optimal system-wide technical efficiency; and 4) ADMUs identified as influential (Seaver and Triantis, 1992) could define what constitutes best practices and/or representative paths to the frontier and or unusual production conditions. In terms of decision-making these premises infer a management system behavior described earlier as risk avoidance or hedging (alignment), adherence to collective best practices (cohesion) and a combination of two. These are, of course, not the only insights that can be gained through the use of this new capability but these are the insights that will be used to both illustrate and test the capability. If this capability is shown to be promising efforts can be made to both generalize (i.e., experiment with other metaphors) and refine the capability (i.e., incorporate a dynamic EF) through future research.

As simulation experiments are conducted it is expected that each agent will be examined for patterns of individual behavior. It is expected that this behavior will conform to the combined goals, rules, percepts, actions and interactions of the CAS flocking metaphor and the DEA form of efficiency analysis. Beyond individual behaviors it is expected that collective behaviors will mimic the flocking of birds as they shift and change direction or choose collectively to metaphorically lite or land in the same tree or lite together along on a convenient set of real world power lines, analogous to the DEA efficient frontier. Using this capability a management system would expect to see the advantages of sharing information across the system and otherwise operating in ways consistent with the coordinated motion. Having implemented the alignment rule the system would expect to preclude any one of its components from making a major or even catastrophic mistake. Upon implementation of this approach the resulting behaviors will confirm or refute this expectation. Having implemented the cohesion rule the system would expect to see all of its components emulate the decisions of the most efficient of its members adjust their policies in each increment of time to eventually achieve a maximum technical efficiency and graphically reach a location on the EF.

3.3.2 Detecting Emergent Patterns of Behavior in CAPEM

A fourth major insight may or may not be achieved. Emergence occurs when system components interact with each other and with information provided by the CAS ABM environment (Holland, 1995). The ADMU symbols used by the CAPEM CAS ABM simulation are active dashboards providing a number of pieces of information on each system component and on the system as a whole, showing the change in their state (location, direction, velocity) over time which in turn indicates changes in the elements of analysis (productive efficiency) over time. It is through these active graphical displays and thorough analysis of data that it will be possible to detect a level of emergence beyond flocking. The next level of emergence may, for example, be recurring patterns or archetypes in the way flocking agents (power plants) make decisions. The search for the next level of emergence might entail looking for patterns such as those identified in system dynamics modeling, i.e., drifting goals or limits to growth (Kim, 2000).

Experimentation using the CAS ABM simulations, is expected to enable researchers to gain and provide insights for a range of conditions (i.e., low to high degree of alignment, low to high degree of cohesion, varying degrees of decision-maker adaptability) under which a policy of both alignment and cohesion might lead to either increased efficiency or achieve the same efficiency in less time. Sensitivity analysis across degrees of alignment, cohesion and adaptability as well as alternative representations of the production axioms are possible with this new capability.

It is expected that patterns will emerge in the way ADMUs reaches the EF. As the population of system components moves toward the EF CAPEM will enable investigation into if and how certain variables effect the changes more than others.

Output displays will provide indications of certain patterns of change under certain conditions as they lead to steady-state behaviors. Also indicated will be individual or collective behaviors success or failure to achieve steady-state behaviors. Although CAPEM simulates complex, non-linear behaviors and provides considerable new insights, it is unlikely that it will immediately reveal the emergence of a single simplified pattern that explains all management system behavior. Complexity science is constantly on the lookout for such patterns but has not yet discovered an eloquent theory of everything of all forms of complex. Until it does it cannot yet forecast when analytic methods such as CAPEM will determine a new level of emergence behavior beyond the metaphor being used, in this case the flocking metaphor (Lewin, 1999). Even when patterns are observed, it is challenging to know, without extensive additional research, if the patterns are truly and repeatedly predictive of system behavior. It will necessary then to be particularly perceptive and creative in observing and describing all possible patterns of behavior among the components of the management system.

4 Notation and Formulations

Dougherty, Ambler and Triantis (2014a) and Chapter 3 above, provided the associative inferences or conceptual linkages associating the building blocks of the complex adaptive systems (CAS) metaphor known as “flocking” as defined by Reynolds (1987), with the building blocks of Data Envelopment Analysis (DEA) as described by Cooper, Sieford and Tone (2007). The resulting bridging methodology was named the Complex Adaptive Productive Efficiency Method (CAPEM). This discussion now moves to the task of expressing CAPEM mathematically and graphically and implementing it in a CAS agent-based model (ABM) simulation. This notation adopts the constrained generating procedure (CGP*)* notation (Holland, 1999) to identify the fundamental elements of the methodology and adopts the NetLogo agent-based modeling (ABM) simulation platform along with validated formulations of the CAS flocking metaphor as implemented by Uri Wilensky of the Northwestern University Center for Connected Learning and Computer-Based Modeling (Wilensky, 1999). This research implements the DEA Production Probability Space (PPS) as a CAS ABM environment, the DEA Decision-Making Unit (DMU) as a CAS ABM agent and the DEA Efficient Frontier (EF) as a component of the PPS. It employs the CAS ABM inter-agent communication capabilities to represent interaction among components of the management system being studied. By developing appropriate mathematical formulations for the associative inferences described in Chapter 3 and by implementing them in a CAS ABM simulation it provides a robust new means of analysis of productive efficiency.

4.1 CAPEM – Formulations

4.1.1 Use of the Constrained Generating Procedure Notation

Holland (1999) provides a notation that is very useful in explaining the implementation of CAPEM in the CAS ABM paradigm. He explains that constrained generating procedure, CGPs, (C) are a broad set of models (i.e., agent types, agent environments, simulation interfaces) that enable the capture of the dynamics of a set of component mechanisms, (i.e., an instance of an agent environment, individual agents, agent communication). CGPs can also describe the allowed interactions that enable and constrain these mechanisms, much as gaming rules both enable and constrain game board configurations. CGPs such as individual agents/individual DMUs (C_{DMU}) are made up of mechanisms (F) (i.e., agent goals, rules, percepts, actions) that are in turn made up of sub-mechanisms (f) (i.e., subordinate variables, parameters, reporting functions, display functions) in strict hierarchies. Mechanism and sub-mechanisms are in fact transformation functions or algorithms that represent cause and effect relations between transformation function inputs and the states of the mechanism. The CGP notation is used to establish the descriptive precision needed to communicate effectively about our models as well as generate and capture, at the necessary level of granularity, the data generated by the simulation. Holland (1999, p.174) asserts that ultimately this level of precision will enable us to detect and differentiate emergent from non-emergent behaviors in the CAPEM CAS ABM environment. Because of the exploratory nature of this research it does not yet purport to describe here emergent behaviors but employ the notation for its descriptive clarity and in anticipation of discovering and expressing emergent properties in future research.

In this notation the CAPEM CAS ABM simulation (C_{SIM}) is composed of a finite set of CGPs, which are the simulation interface (C_{INT}), the agent environment (C_{ENV}), the population of CAS ABM agents representing the DEA decision-making units (C_{DMU}), the CAS flocking metaphor itself (C_{FLK}) and the DEA EF (C_{EF}). This chapter provides descriptive notation for each of these CGPs.

Table 4-1. Elements of the CGP Composing the CAPEM Simulation

CGP (C)	Description
$C_{SIM} = (C_{INT}, C_{ENV}, C_{EF}, C_{DMU}, C_{FLK},)$	The simulation is a strictly closed system made up of *CGP* for the simulation interface, the agent environment, the DEA Efficient Frontier, the population of agents, and the rules that make up the CAS flocking metaphor and the DEA axiomatic framework..

4.1.1.1 Combining CGPs

A small set of rules govern the combination of CGPs are needed to form more and more complex CGP appropriate to the research. These are summarized as follows:

1. A *CGP* can be made up of one or more mechanisms *(F)* which themselves can be made up of one or more sub-mechanisms (*f*).
2. Adding a new mechanism or sub-mechanism to an existing *CGP* creates a new *CGP* (C’)
3. Existing *CGPs* (C and C’) can be connected forming a new *CGP* (*C*”)
4. All *CGP*s *(C)* are formed via combinations of existing CGP

5. *CGPs (C)*, mechanisms (*F*) and component mechanisms (*f*) can be assigned unique identifiers, index numbers.

In accordance with rule 1 above all $C = (F_1, F_2, \ldots, F_h)$ and all $F = (f_1, f_2, \ldots, f_m)$ where f_h is a transformation function that is affected by inputs, which cause a change in the state of the mechanism or sub-mechanism.

Each mechanism (F_h) and sub-mechanism (f_h) is defined by it inputs (I_h) and its states (S_h), hence, $f_h : I_h \times S_h$, where $I_h = I_{h1} \times I_{h2} \times \ldots. I_{hk(h)}$ designates the possible inputs to sub-mechanism h and where k(h) is the number of inputs to sub-mechanism h and $S = S_1 \cup \ldots \cup S_m$. CGP are connected by matching inputs between and among mechanisms. In any combination of CGP there will be inputs that are already connected to other mechanisms (I_{hconn}) and those that are not connected or free (I_{hfree}). Ultimately, the combined CGP can be described as a single aggregate transformation function f_C: $I_c x S_c$, where S_c is the product of the state sets of each of the mechanisms and sub-mechanisms and I_c is made up of all possible inputs.

4.1.1.2 Interfaces Between and Among CGPs

The interfaces between these CGPs are defined by a set of interface functions defined as: $g_{ij}\ ;\ S \rightarrow I_{ij}$ that associate a particular input *j*, with a particular mechanism *i*. Recall that each mechanism may have a unique set of allowed inputs. Mechanism h is connected to input j of mechanism *i* when, for all times *t*, $I_{ij(t)} = g_{ij}(S_{h(t)})$. This interface function (g_{ij}) applies to subject domains with a fixed geometry, that is, a set of mechanisms where the interface can be predefined and does not change throughout the simulation. The mechanisms that were used to implement the illustrative scenario used in this research are of the fixed geometry category. Holland (1999) also describes a variable form of the interface function, which can be applied to a broader set of problems and provides additional computational capabilities. The purpose of this chapter is to describe this notation, demonstrate the versatility of the notation and establish it value for future research.

The variable form of the interface is achieved by matching mechanisms (f_n) with inputs that are free (I_{hfree}) (have not been previously matched). with other mechanisms that have input conditions that are free. CGP construction rule #4, above, for new CGP construction is accomplished through this matching of free inputs with open input conditions. Upon instruction from another component mechanism (f_h) these connections can be broken and reformed. The component mechanism (f_h) of any of these descriptors can, in fact, call on any other descriptor and process it as an input in accordance with the above rules of CGP construction. Precisely defining and indexing CGPs, mechanisms and component mechanisms as inputs and states using these rules and a standardized form of descriptors, described in the next paragraph, will enable us in future research to "completely determine the dynamic behavior of the composite macro-mechanism" (Holland, 1999, p. 167) an essential capability in discovering CAS emergence.

4.1.1.3 Standardized Descriptors

To more fully describe each mechanism and each sub-mechanism this notation employs a standardized descriptor that adheres to the CGP rules and relationships. This standardized descriptor provides structure with which to enumerate the necessary inputs and states and then adds unique identifiers for both the descriptor itself and for the transformation function involved. The resulting standardized descriptor is described in Table 4-2 below.

Table 4-2. Standardized Descriptor for Mechanisms and Sub-Mechanisms – Generic Format

Unique binary identifier for this descriptor	Unique binary identifier for the transfer function being employed	Inputs 1 …n	The internal state of the transformation function used by this mechanism or submechanism

This structure becomes useful in enabling a researcher or analyst to assemble a complete list of standardized descriptors for all components (mechanisms and submechanisms) which form a "current component list (ccl)" or when all states are specified, the "current state list (csl). As explained further in Section 4.1.1.1 above, the ccl or csl permit the construction system specifications sufficient for a general computing machine or readily translatable to any other computer language. Execution of each transformation function contained in this list, in accordance with the CGP rules of construction, in each increment of simulation time would if necessary constitute the simulation.

4.1.1.4 An Illustrative Example

The tables below, are provided for illustrative purposes and provide samples of a CGP notation for the CAPEM simulation interface. Table 3 lists the mechanism and sub-mechanisms required to form the CAPEM simulation interface (C_{INT}). Tables 43 through 4-7 provide examples of standardized descriptors that elaborate on mechanisms and sub-mechanisms of this CGP. Additional information on these descriptors and how they are implemented in CAPEM is described in Appendix A, Summary Descriptions of the CAPEM NetLogo-Based Code.

Table 4-3. Elements of the *CGP* for the CAPEM Simulation Interface, C_{INT}

CGP/Mechanisms	Description
C_{INT} = ($F_{INT0101}$, … , F_{INTij})	The simulation interface is composed of the functions and sub-functions shown below (number of the mechanism = *i* = (00-99) (number of the sub-mechanism = *j* = (0-10)

FINT01	Define Global Variables (Initial Number of Agents, Minimum Separation Distance, Maximum Separation Turn, Sorted-EF, Alpha, Beta, Constant)
FINT02	Define Agent Types (Inefficient ADMUs, Efficient ADMUs)
FINT03	Define Characteristics of All Agents (Heading From the Origin, Technical Efficiency)
FINT04	Define Characteristics of All Inefficient ADMUs (peers, flockmates, nearest neighbor, production-function-value)
FINT05	Clear the Agent Environment (Reset all global variables to zero, and executes the following commands: clear-ticks, clear-turtles, clear-patches, clear-drawing, clear-all-plots, and clear-output.)
FINT06	Choose Method of Setup – Fully Random or Manual (Using an Input File)
FINT07	Set Up the Agent Environment-Manual
fINT0701	Select the Random Number Seed
f INT0702	Assign x and y coordinates to agents from a data file
f INT0703	Instantiate Each Inefficient ADMU in the environment (by setting the color, shape, size, initial x-coordinate, initial y-coordinate, initial value of the production function)
CGP/Mechanisms	**Description**
FINT08	Set Up the Agent Environment-Random
fINT0801	Select the Random Number Seed
fINT0802	Assign x and y coordinates to agents randomly
fINT0803	Calculate Heading From the Origin-Input-Oriented
Note: Identifying the EF is a separate CGP due to its complexity	
FINT09	Draw Efficient Frontier
fINT0901	Identify the Efficient ADMU
fINT0902	Create Artificial ADMUs on Right Boundary of the Agent Environment (DEA PPS) perpendicular to the Lower-Most Efficient ADMU and on Upper Boundary of the Agent Environment (DEA PPS) perpendicular to the Left-Most Efficient ADMU
fINT0903	Sort the ADMUS that Define the Efficient Frontier

$f_{INT0904}$	Connect the Efficient ADMUS with lines between them
FINT10	Simulate
FINT11	Draw Technical Efficiency Graph
FINT12	Display Technical Efficiency Graph

Note that the other CGP in the simulation will, of course, need to work in conjunction with this CGP to execute the simulation.

Table 4-4. Descriptor for Setup of the Environment Using an Input File, F_{INT07}

Unique Binary Identifier for this Descriptor	Unique Binary Identifier for the Transformation Function Involved	Input 1	Input 2	Input 3	Input 4	Input 5
00000000	10000000	Random or Manual	Random Number (selected randomly or manually selected)	Input Filename	xcoordinate	y-coordinate
		Input 6	**Input 7**	**Input 8**	**Input 9**	**State**
		Color	Shape	Size	Heading From the Origin	State of the Transformation Function described below.

The transformation function (10000000) in this mechanism is the simulation command “to SETUP-ADMUS” which begins a sequence of steps and commands that prepare the simulation for execution of an experiment. Since F_{INT07} = ($f_{INT0701}$, $f_{INT0702}$, $f_{INT0703}$), this descriptor is an aggregate of the following three descriptors.

Table 4-5. Descriptor for Selecting the Random Number Seed, f $_{INT0701}$

Unique Binary Identifier for this Descriptor	Unique Binary Identifier for the Transformation Function Involved	Input 1	Input 2	Input 3	State
00000001	10000001	Random or Manual	Seed Selected randomly or self-selected	Changing or Repetitive for each Experiment	State of the Transformation Function described below.

The simulation command for this mechanism is “if (Own-Seed! = "Systemchosen-seed") [random-seed Own-Seed]” which results in the use of a random number seed that is selected by the experimenter and used for all runs of the experiment.

Table 4-6. Descriptor for Assigning x and y coordinates to agents from a data file, f $_{INT0702}$

Unique Binary Identifier for this Descriptor	Unique Binary Identifier for the Transformatio n Function Involved	Input 1	Input 2	Input 3	State
00000010	10000010	Data file name	x-coordinate from file	y-coordinate from file	State of the Transformation Function described below.

The simulation code for this function is “file-open “myfile_random_input_inefficient_admus.txt"” which simply opens the file and brings into the simulation a partially instantiated population of ADMUs with matched x-coordinates and y-coordinates but without yet assigning them to individual ADMU.

Table 4-7. Descriptor for Setting the Characteristics of a Population of Inefficient DMUs, $f_{INT0703}$

Unique Binary Identifier for this Descriptor	**Unique Binary Identifier for the Transformation Function Involved**	**Input 1**	**Input 2**	**Input 3**	**Input 4**	**Input 5**
00000011	10000011	Color	Shape	Size	Initial x-Coordinate	Initial y-Coordinate
		Input 6	**Blank**	**Blank**	**Blank**	**State**
		Initial Value of the Production Function				State of the Transformation Function described below.

The simulation code for this function is “ask inefficient-admus” which assigns to each ADMU the list of characteristics shown as inputs in the descriptor, including the x and y coordinates drawn from the list produced by the previous function thus fully instantiating all simulation ADMUs in their initial state.

This example while somewhat trivial illustrates the use of the CGP notation to fully specify the simulation. As illustrated $C_{INT} = \sum F_{INTij}$ and $F_{INTij} = (\sum f_{INTij})$. The descriptor for F_{INTij} is an aggregate of the subordinate mechanisms f INT0101 … f_{INTij}. Employing the small set of mechanisms that make up C_{INT} and the other CGP that compose C_{SIM}, a computer can be programed to instantiate the CAPEM simulation interface, be it a general purpose computer, a computational mathematics model or a higher order simulation language such as NetLogo.

4.1.1.5 Traceability of Agent Behavior

Holland (1999) affirms that this notation is sufficiently precise and sufficiently robust to form, if necessary, a general computing machine and advocates for its use in a massively parallel processing environment to trace precisely agent behaviors and increase the likelihood of differentiating between expected, computable behaviors and emergent behaviors. This is accomplished by assembling a complete list of standardized descriptors for all components (mechanisms and submechanisms) of a simulation. This list is called the “current component list (ccl)” or when all states are specified, the “current state list (csl). Execution of each transformation function contained in this list, in accordance with the CGP rules of construction, in each increment of simulation time constitutes the simulation.

An indexed set of CGPs, mechanisms, and sub-mechanisms described entirely by their inputs and their states have been used by another member of the complexity community that uses this notation, John Conway to fully specify and construct a simulation boldly named “Life” (Holland, 1999). In “Life” a number of patterns (cellular automata) emerge, interact and evolve, from a checkerboard-like configuration made up of just 8 inputs and 2 states. Holland (1999) uses this notation himself to fully specify and construct a simulation he calls Echoing Emergence (Echo) in which he demonstrates the capabilities of genetic algorithms. This notation enables representation of behaviors that replicate, combine, mutate and evolve the initial resource mechanisms (system components) into to well-formed, complex, aggregate organism. Use of cellular automata and genetic algorithms are outside the scope of this research but use of the same powerful notation to completely determine the behaviors of management systems will greatly facilitate the future development of a CAS approach to productive efficiency analysis. CGPs, mechanisms and component mechanisms are ideal for describing and representing the associative inferences between the building blocks of CAS ABM and DEA in CAPEM, which are then implemented in the NetLogo CAS ABM simulation platform.

4.2 Implementing the Building Blocks of CAS ABM and DEA in CAPEM

4.2.1 Defining a Management System in CAPEM

The label "ADMU" is used to designate the DEA DMU represented as CAS ABM agents. In CGP notation the CAPEM ADMU is represented as a CGP (C_{DMU}) made up of the mechanisms and sub-mechanisms shown in Table 4-8 below. The management system is then defined as the population of ($C_{DMU0101}$ … C_{DMUij}). The mechanisms and sub-mechanisms that compose the functionality of the population of ADMUs are presented in Table 4-8, below.

Table 4-8. Elements of the *CGP* Composing the CAPEM Agent Population, C_{DMUij}

CGP/Mechanisms	Description
C_{DMU} = ($F_{DMU0101}$, … , F_{DMUij})	Individual agents are composed of the functions shown below (number of the mechanism = *i* = (00-99) (number of the sub-mechanism = *j* = (0-10)
F_{DMU01}	Intersect EF (Agent Goal)
F_{DMU02}	Report Goal Reached (Agent Action)
F_{DMU03}	Report Location (Agent Action)
F_{DMU04}	Find Flockmates (Agent Percept)
F_{DMU05}	Find Neighbors (Agent Percept)
$f_{DMU0501}$	Find Nearest Neighbor
F_{DMU06}	Calculate-Heading-Input-Oriented
$f_{DMU0601}$	Determine-Average Flockmate Heading-X-Component

$f_{DMU0602}$	Determine-Average Flockmate Heading-Y-Component
$f_{DMU0602}$	Determine-Average Heading Toward Peers, X-Component
$f_{DMU0603}$	Determine-Average Heading Toward Peers, Y-Component
F_{DMU07}	Determine the Technical Efficiency
F_{DMU08}	Calculate Optimum Production
CGP/Mechanisms	**Description**
F_{DMU09}	Locate Peers

Note that the CGP for the flocking metaphor will be combined with this CGP to fully define each ADMU.

ADMU goals, percepts and actions introduced in a previous paper (Dougherty, Ambler and Triantis, 2014a) and Chapter 2 above, are listed. The ADMUs ability to maintain awareness of its flockmates and peers, calculate its heading, its technical efficiency (TE) and its own optimum output production is described. The following standardized descriptors provide illustrative examples of how the notation further elaborates on the information provided in Table 4-8, above.

Table 4-9. Descriptor for Intersecting the DEA EF (an ADMU Goal), F_{DMU01}

Unique Binary Identifier for this Descriptor	Unique Binary Identifier for the Transformation Function Involved	Input 1	Input 2	Input 3	State
00000100	10000100	x-coordinate for ADMU	y-coordinate for ADMU	Line defining the EF nearest the ADMU	State of the Transformation Function described below.

This descriptor in Table 4-9 above, elaborates on a mechanism that represents an agent goal. The mechanism has no sub-mechanisms. The simulation code for the transfer function involved executes the command “to-report intersect-ef [*x y*]” resulting in a calculation of the difference between the location of the ADMU and the location of the DEA EF, if any. When the difference is equal to zero the ADMU has reached its goal.

Table 4-10. Descriptor for an ADMU Finding Its Nearest Flockmate (an ADMU Percept), $f_{DMU0501}$

Unique Binary Identifier for this Descriptor	Unique Binary Identifier for the Transformation Function Involved	Input 1	Input 2	Input 3	State
00000101	10000101	Location of ADMU	Location of All Flockmates	Distance to Each Flockmate	State of the Transformation Function described below.

This descriptor in Table 4-10 above, elaborates on a sub-mechanism that represents an agent percept. The simulation code for this transformation function is “to find-nearest-neighbor” which scans a list of all neighbors for this agent and determines which is nearest. The list of all neighbors used in this function was determined by execution of a previous mechanism (C_{ADMU}, Table 4-8 above). This sub-mechanism and the previous mechanism constitute an agent’s ability to sense or perceive. Recall that an agent’s percepts are the inputs it selects from the agent environment on which it makes decisions. Knowing its nearest neighbor and agent can in accordance with the rules of flocking, maintain separation and avoid collision with its neighbors as a part of the flocking behaviors. The state of the function is the state of the list of the identities of its flockmates and the minimum distance to the other ADMUs/flockmates.

Table 4-11. Descriptor for Determining the TE for each ADMU, F_{DMU07}

Unique Binary Identifier for this Descriptor	Unique Binary Identifier for the Transformation Function Involved	Input 1	Input 2	Input 3	State
00000110	10000110	Distance from origin to the ADMU	Distance from origin through ADMU to the Intersection with the EF	Blank	State of the Transformation Function described below.

This transformation function in Table 4-11 above, is composed of a single subfunction which executes the command "to show-tech-efficiency" resulting in a calculation of the technical efficiency which is also a measure used in CAPEM to define the relative state of the ADMU among its peers. Technical efficiency is determined as follows: (distance-origin-to-projection) / (distance-from-origin).

4.2.2 Defining Management System Policy (the flocking metaphor) in CAPEM

As has been described previously, the aggregate management policy chosen by the leadership of this management system is to adhere to the CAS flocking metaphor. DMUs within the management system flock, align, cohere and separate as defined in Table 4-12, below.

Table 4-12. Elements of the *CGP* Composing the Flocking Metaphor, C_{FLK}

CGP/Mechanisms/ Sub-Mechanisms	Description

$C_{FLK} = (F_{FLK0101}, \ldots , F_{FLKij})$	The CGP representing the Flocking Metaphor is composed of the functions and sub-functions shown below (number of the mechanism = *i* = (00-99) (number of the sub-mechanism = *j* = (00-10)
F_{FLK01}	Flock
CGP/Mechanisms/ Sub-Mechanisms	**Description**
$f_{FLK0101}$	Find Flockmates
$f_{FLK0102}$	Find Nearest-Neighbor
$f_{FLK0103}$	Determine if the Nearest Neighbor is less than the desired Separation Distance
F_{FLK02}	Separate (Agent Rule)
$f_{FLK0201}$	Determine the Maximum Separation Angle
$f_{FLK0202}$	To Turn Away
$f_{FLK0203}$	To-Turn-At-Most
F_{FLK03}	Alignment (Agent Rule)
$f_{FLK0301}$	Determine the Maximum Alignment Turn
$f_{FLK0302}$	To Turn Toward
$f_{FLK0303}$	To Turn-At-Most
F_{FLK04}	Cohesion (Agent Rule)
$f_{FLK0401}$	Determine the Maximum Cohesion Turn
$f_{FLK0402}$	To Turn Toward
$f_{FLK0403}$	To Turn-At-Most
F_{FLK02}	Determine the Value of the Production Function

Table 4-13. Descriptor for Alignment (an ADMU Rule), F_{FLK03}

Unique Binary Identifier for this Descriptor	Unique Binary Identifier for the Transformation Function Involved	Input 1	Input 2	State
00000111	10000111	Average Flockmate Heading	Maximum Alignment Turn	State of the Transformation Function described below.

This descriptor in Table 4-13 above, elaborates on an agent rule, the flocking rule to align. To do so an ADMU must determine the average flockmate headings, described in Table 4-14 below. As this ADMU seeks to attain the average flockmate heading it is constrained by the input value for the maximum allowed alignment turn. The maximum alignment turn input value is set by the experimenter based on knowledge of the ADMUs ability to change its policies in a single increment of time. The state of this transformation function is the total change in heading in degrees an ADMU will make in an increment of time to align with flockmates.

Table 4-14. Descriptor for Determining the Average Flockmate Heading, f_{FLK03}

Unique Binary Identifier for this Descriptor	Unique Binary Identifier for the Transformation Function Involved	Input 1	Input 2	Input 3	State
00001000	10001000	*x*-component of flockmates	*y*-component of flockmates	Heading from the origin	Current state of the Transformation Function described below.

The function involved in this sub-mechanism is executed in the simulation by the command “to-report average-flockmate-heading”.

The x-component is calculated as: $\sum_{i=1}^{n} \sin(\text{heading of ADMU}_i)$. The y-component is calculated as: $\sum_{i=1}^{n} \cos(\text{heading of ADMU}_i)$. In its effort to attain the average flockmate heading it is constrained by the input value for the maximum alignment turn. Maximum alignment turn is set by the experimenter based on knowledge of the ADMUs ability to change its policies in a single increment of time. The average flockmate heading is calculated as the arctangent of x and ycomponents of flockmates which is expressed in degrees from the x-axis. Further elaboration of this CGP is included in the appendices section A.1.3. For detailed elaboration on these procedures refer to Welinsky (1999) and Tanner, Jadbabaie and Pappas (2003).

4.2.3 Adaptability in CAPEM

Employing a NetLogo convention (Wilensky, 1999), CAPEM constrains the maximum amount of change a system can achieve in a single increment of time. This is highly intuitive concept has obvious parallels in any complex management system. Any system has a limit to its ability to adapt to change. These limitations could take the form of constrained funding, time limitations, limitations on the ability to staff, retain or retraining staff, as well as the physical limitations of facilities, technology replacement or other constraints. A federal agency may, for example, have real limitations on its ability to adapt due to constraining legislation and or inflexible internal procedures. The ability of one management system to achieve the average direction and velocity (alignment) of its flockmates may be constrained. The degree of flexibility of a management system to adapt to the average position of its peer set (cohesion) may be different than its ability to align, hence the value in having two distinct variables. In the CAPEM implementation the values of these variables are set by the user at the outset of the simulation.

Table 4-15. Descriptor for Maximum Alignment Turn, $f_{FLK0303}$

Unique Binary Identifier for this Descriptor	Unique Binary Identifier for the Transformation Function Involved	Input 1	Input 2	Input 3	State
00001001	10001001	Max-turn parameter from C_{INT}	ADMU Current Heading	ADMU New Calculated Heading	State of the Transformation Function described below.

The function in Table 4-15 above, involved in this sub-mechanism is executed in the simulation by the command “to turn-at-most [turn max-turn]”. Employing a NetLogo convention (Wilensky, 1999), CAPEM defines an explicit variable for the distance at which an agent separates to avoid collision. The resulting state of the submechanism sets the absolute value of the limit of turn allowed to avoid collision regardless of other factors. The separation behavior takes precedence over the alignment and cohesion behaviors, as evident in the NetLogo flocking procedure. Just as the ability of a system to align or cohere is limited, the ability of a system to avoid collisions is constrained by any number of scenario-based factors. The notion of a collision of two management systems may translate to competition for scarce resources, such as a need to use the same equipment, share a labor force or source of power. In CAPEM, where the location of a ADMU on the production possibility space is defined in terms of technical efficiency the interpretation of a collision is a bit more abstract. For two management systems to have the same technical efficiency may have no meaning at all, again, depending on the scenario. If this is the case the analyst simply sets these two factors to zero. Because of the exploratory nature of this research simulations were conducted with separation distance and turn set at higher values to get a sense of their effect on the behavior of the management system.

The concept of separation and these implementations may prove to be of significant value for decision-makers when using this metaphor.

Table 4-16. Descriptor for Minimum Separation Turn, f $_{FLK0203}$

Unique Binary Identifier for this Descriptor	Unique Binary Identifier for the Transformation Function Involved	Input 1	Input 2	Input 3	State
00001010	10001010	Current Heading	Heading of Nearest Neighbor	Maximum Separation Angle	State of the Transformation Function
Unique Binary Identifier for this Descriptor	**Unique Binary Identifier for the Transformation Function Involved**	**Input 1**	**Input 2**	**Input 3**	**State**
					described below.

The function in Table 16 above, involved in this sub-mechanism is executed in the simulation by the command "to turn-away ([heading] of nearest-neighbor) Maximum-Separation-Angle". When the distance between an ADMU and its nearest neighbor reaches a defined minimum threshold (determined by the separate mechanism, F_{FLK02}) the ADMU will turn to increase it distance. It will turn away as far as it is able which is set by the input value in degrees of the experimenter-defined parameter Maximum Separation Turn. The state of the transformation function is the new ADMU heading.

4.2.4 Defining the Agent Environment (the DEA PPS)

As described by Cooper, Sieford and Tone (2007), the production possibility space (PPS) is a key management system concept. A management system naturally seeks to optimize technical efficiency of all system components (e.g., individual power plants) at any point in time and to, as soon as possible, achieve maximum productive efficiency for all system components. The DEA PPS for output-oriented and input-oriented experiments is shown as the area bounded by the axes and by the dotted lines opposite the axes in Figures 2-4-1 and 4-2, respectively.

Figure 4-1a. The Production Possibility Set – Output Maximization

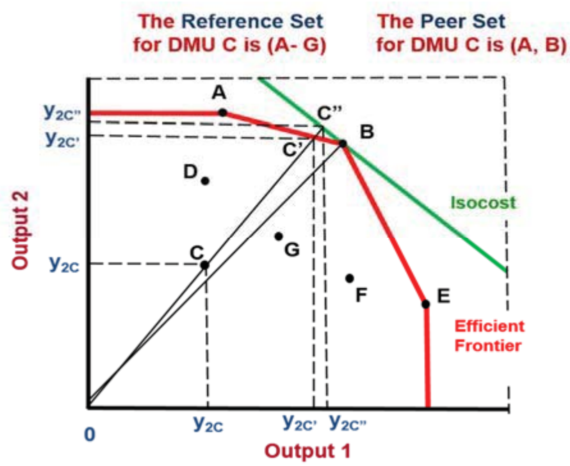
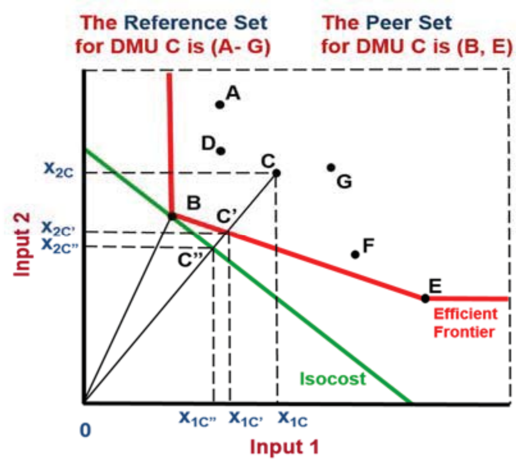


Figure 4-1b. The Production Possibility Set – Input Minimization



The PPS is defined by the mechanisms and sub-mechanisms for C_{ENV} shown in Table 4-17, below. The individual ADMUs that make up this population are shown as white arrowheads in these figures and are defined by C_{ADMU} in Table 4-15, above. The piecewise linear curves shown as red lines represent the DEA EF and are defined by C_{EF} in Table 4-17, below. The blue lines illustrate the radial measures used to calculate technical efficiency as defined in Table 4-8, above. By interacting, these CGPs implement the CAPEM simulation. Each ADMU has a heading, represented by the direction of the arrow and a speed, represented by distance traveled in any given increment of time. As a CAPEM experiment the PPS must be defined with sufficient size to encompass all feasible maximums of all inputs and output data in the experiment. The two dimensional, positive coordinate space in the CAPEM implementation, with origin zero, ensure that all production combinations are real valued combinations of inputs and outputs. The origin, the axes and a properly chosen maximum value for each input and output dimension become the natural boundary for the space. In CGP notation the PPS (C_{ENV}) is composed of mechanisms that create the (patches) (F_{ENV01}) and defined the measures of time.

Table 4-17. Elements of the CGP Composing the Agent Environment (the DEA PPS), C_{ENV}

CGP/Mechanism	Description
C_{ENV} = ($F_{ENV0101}$, … , F_{ENVij})	The agent environment is composed of the functions shown below (number of the mechanism = i = (00-99) (number of the sub-mechanism = j = (0-10)
F_{ENV01}	Define Units of Space (Patches, in pixels)
F_{ENV01}	Define Units of Time (Ticks)
F_{ENV01}	Create DMUs
$f_{ENV0101}$	To Set Location (x, y)
$f_{ENV0101}$	To Set Production Function Value

Interactions between ADMUs (C_{ADMU}) and the PPS (C_{ENV}) represent the interactions between individual ADMU and the patches within the PPS.

Table 4-18. Descriptor for Creating ADMUs within the PPS, F_{ENV01}

Unique Binary Identifier for this Descriptor	Unique Binary Identifier for the Transformation Function Involved	Input 1	Input 2	Input 3	Input 4
00001100	10001011	*x*-coordinate	*y*-coordinate	color	shape

	Input 5	Input 6	Input 7	State
	size	Production Function value	color scale	State of the Transformation Function described below.

As described previously in Tables 4-6 and 4-7 above the x-coordinates and y-coordinates for each ADMU is read into the simulation from a data file and a full set of individual ADMU characteristics were defined. Through this mechanism acting in conjunction with the previous mechanisms, each ADMU is given a unique number, placed in the PPS and is accessible by the supporting tools provided by the simulation platform. The simulation code that implements this mechanism is "create-inefficient-admus 1…n". The state of this transformation function is the fully defined ADMU properly instantiated in the PPS.

Table 4-19 below stipulates that the PPS is composed of all positive real numbers for both inputs and outputs. This stipulation is enforced in the simulation by the dimensions defined for a platform structure called the "world".

Table 4-19. Possible States of the DEA PPS in CAPEM

Element	Notation	Description
Input Space	$\Re_{M+}$	All positive real numbers
Output Space	$\Re^N_+$	All positive real numbers

The axes formed by the patches are divided into units of measure consistent with the subject domain. In the power plant scenario described in Chapter 5, the axes of the PPS are divided into British Thermal Units (BTU) for fuel, full time equivalents (FTE) for labor, kilowatts for energy used as an input and megawatts for electrical power output. Generic units of length in the NetLogo simulation are the width and height of rectangles called “patches”. The analyst defines the mapping of units of measure to patches.

4.2.5 The DEA Efficient Frontier

The DEA EF is also a key management system property. As defined by Cooper, Sieford and Tone (2007), and as its name implies, the efficient frontier is at the extreme edge of the population of ADMUs. Its location is determined by the input conditions and states of a set of the most efficient ADMUs. Identifying and utilizing the EF in a simulation and remaining true to its definition in DEA is challenging.

Consequently the EF is defined as its own CGP. The left-most ADMU in the population is by definition the ADMU that is using the least amount of the first factor of production. The lower-most ADMU in the population is likewise the ADMU using the least amount of the second factor of production. The approach is to start with lower-most and left-most ADMU to systematically identity the sub-set of ADMU that fully define the extreme edge of the ADMU population.

Any ADMU inside a triangle formed by 1) the vertical line running though the left-most ADMU, 2) a vertical line running through the lower-most and 3) a hypotenuse connecting the two isolates the remaining sub-set of ADMUs that potentially lay on the extreme boundary of the population (those ADMUs that potentially use the least combination of the inputs). In simple cases the identification of the next left-most and lower-most ADMUs is straightforward and through iteration finally narrows to either zero of one remaining ADMU. With some additional checks for special cases the mechanisms and sub-mechanisms in C_{EF}, shown in Table 4-20, below completes the selection of the ADMU that fully defines the DEA EF for each experiment.

Table 4-20. Elements of the CGP for Identification of the DEA EF, C_{EF}

CGP/Mechanisms	To identify the EF [input-oriented]
C_{EF} = (F_{EF0101}, … , F_{EFij})	The CGP the identifies and implements the DEA Efficient Frontier is composed of the mechanisms and sub-mechanisms shown below. (number of the mechanism = *i* = (00-99) (number of the sub-mechanism = *j* = (00-10)
F_{EF01}	To find left-most inefficient ADMU
F_{EF02}	To find lower-most inefficient ADMU
F_{EF03}	To find left-most-lower-most inefficient ADMU
F_{EF04}	To find lower-most-left-most inefficient ADMU
F_{EF05}	To Make Efficient Lower-Most ADMU
CGP/Mechanisms	**To identify the EF [input-oriented]**
F_{EF06}	To Make Efficient Left-Most ADMU
f_{EF0601}	To Designate Lower-Most ADMU as a Temporary ADMU
f_{EF0602}	To Identify the Temporary ADMU with the minimum y-coordinate
f_{EF0603}	To Designate Left-Most ADMU as a Temporary ADMU
f_{EF01}	To Identify the Temporary ADMU with the minimum x-coordinate
F_{EF07}	To count inefficient ADUs
f_{EF0701}	To Report lower-most
f_{EF0702}	To place selected (now efficient) ADMUs in order
F_{EF08}	To Make Selected Input-oriented Inefficient Efficient
F_{EF09}	To Determine the Number of Inefficient ADMU in the triangle Case 0

f_{EF0901}	To Determine the slope and intercept of the line forming the hypotenuse of the triangle of the input-oriented triangle
f_{EF0902}	To Identify inefficient-ADMUs within the input-oriented triangle
f_{EF0903}	To Identify the Left and Right Most ADMUs
f_{EF0904}	To Identify the Top and Bottom Most ADMUs
F_{EF10}	Determine the Number of Input-oriented Inefficient ADMU in the Triangle Case 1
F_{EF11}	Determine the Number of Input-oriented Inefficient ADMU in the Triangle Case 2
F_{EF12}	Determine the Number of Input-oriented Inefficient ADMU in the Triangle Case 3
F_{EF13}	To Stop

Table 4-21. Descriptor for Finding the Left-Most-Lower-Most Inefficient ADMU, F_{EF03}

Unique Binary Identifier for this Descriptor	Unique Binary Identifier for the Transformation Function Involved	Input 1	Input 2	Input 3	State
00001101	10001100	*x* and *y*-coordinates of the ADMU in the Input-Oriented Triangle	Left-mostlower-most ADMU	Lower-mostleft-most ADMU	State of the Transformation Function described below.

The simulation code for the function contained in the descriptor in Table 4-21 above, is a command to "let left-most-lower-most find-left-most lower-most turtles". The left-most-lower-most refers to the location of ADM in the PPS and identifies the ADMU that uses the least of both factors of production but with leftmost being the priority. This mechanism has a companion command to "let lowermost-left-most find-lower-most left-most-turtles" which finds the ADMU that uses the least of both factors of production but with lower-most being the priority. Previous to the final iteration of this mechanism, the ADMUs identified by each of these commands will be different. Both ADMUs so identified will become candidates for the list of the most efficient ADMUs. As described in Table 4-22, below, only when the two commands identify the same ADMU will the simulation cease iterating to narrow down this list and define the DEA EF. The state of this transformation function will be the identities of the next two candidates to be used to define the EF.

Table 4-22. Descriptor for Stopping Rule for Locating Most Efficient DMU, F_{EF13}

Unique Binary Identifier for this Descriptor	Unique Binary Identifier for the Transformation Function Involved	Input 1	Input 2	State
00001110	10001101	Location of left-most-lower-most ADMU in the population	Location of lowermost-left-most ADMU in the population	State of the Transformation Function described below.

The stopping sub-mechanism described in Table 4-22 above, is performed using a conditional command as follows: "if else left-most-lower-most = lower-most-leftmost [stop]". Only when the left-most-lower-most ADMU equals the lower-most-left-most ADMU will the simulation stop making these comparisons. It is important to understand that this is a direct representation of what is done visually by the analyst in a standard DEA analysis. The two possible states for this function are Stop or Continue to Search.

Table 4-23. Descriptor for Defining the Hypotenuse of the Input-Oriented Triangle, f_{EF0901}

Unique Binary Identifier for this Descriptor	Unique Binary Identifier for the Transformation Function Involved	Input 1	Input 2	Blank	State
00001111	10001110	y-coordinates of the left-most and lower-most ADMU	x-coordinates of the left-most and lower-most ADMU		State of the Transformation Function described below.

At each iteration of this sub-mechanism the approach is to uniquely identify the most efficient ADMU in the population by isolating the ADMUs that meet the criterion. Because of the two-dimensional nature of the PPS the set of candidate ADMUs can be bounded by a right triangle formed by the horizontal line draw through the last identified "left-most-lower-most" ADMU, a vertical line draw through the "lower-most-left-most" ADMU and the hypotenuse joining the these two ADMU. The slope of the hypotenuse is defined by the sub-mechanism shown in the Table 4-23 above as the differences of the x and y-coordinates of the ADMUs involved. m = ((yleft–ylower)/(xleft–xlower)). The state of this sub-mechanism is the value for the slope of the hypotenuse of the Input-Oriented Triangle.

Table 4-24. Descriptor for Finding the ADMU in the Input-Oriented Triangle, f_{EF0902}

Unique Binary Identifier for this Descriptor	Unique Binary Identifier for the Transformation Function Involved	Input 1	Input 2	Input 3	Input 4
00010000	10001111	Vertical Line through RightMost-Lower Most ADMU	Horizontal Line Through Left Most-Upper-Most ADMU	Hypotenuse of InputOriented Triangle	Slope of line forming the triangle

	Input 5	Input 6	Input 7	State
	x-coordinates of all inefficient ADMU	y-coordinates of all inefficient ADMU	Blank	State of the Transformation Function described below.

The new list of candidate ADMUs is made up of those ADMUs found in the space defined by this triangle and by execution of the command “to-report turtles in-triangle [x_1, y_1, x_2, y_2]”. The search for the left-most-lower-most and the lowermost-left-most ADMUs in this population begins again and continues until the stopping rule is satisfied. The state of this sub-mechanism is the number and identification of ADMUs within the triangle.

4.2.6 CAPEM Analog to the CGP Current Component List or Current State List

CGP notation has been used to identify and create a hierarchical organization of the many functions required to implement the building blocks of CAS ABM and DEA that make up the CAPEM simulation. It is important to recall from the description of CGP in Section 4.1.1 above that by documenting and fully elaborating a standardized descriptor for every function and describing each input and state of these functions it is possible, as described by Holland (1999), to produce a complete and comprehensive current component list (ccl) or current state list (csl) for CAPEM. This ccl would be executable as a general computing machine or better yet would, if needed, provide the detail needed for executing CAPEM in a massively parallel computing machine. While these are not within the scope of this exploratory research it is within the objective of this research to be able to begin the process of making this notation comparable with work done by Holland, Conway and other leaders in the study of CAS ABM and emergence (Holland, 1999). For scoping purposes the descriptors have not been specified in sufficient detail to be implemented as a general purpose computer. The choice for this research instead takes advantage of the higher order simulation language and analytic capabilities provided by NetLogo. This form of the descriptors are including in this chapter to be able to communicate with the other researchers that employ the Holland notation and by so doing facilitate future work. Consequently the required transformation functions are specified by within the standardized descriptors by making reference to the NetLogo code. Execution of the interactions among CGPs therefore in reality adheres to the conventions of NetLogo rather than execution of ccl/csl links between free inputs in each increment of time as described in the CGP notation. The value in notating CAPEM using CGP notation together with the NetLogo code for the transformation functions is undiminished, even enhanced, for purposes in this research.

4.2.7 Determining DEA Productive Technical Efficiency

Technical efficiency, as originally defined by Farrell (1957), for each ADMU by comparing its radial distance measured from the origin to an ADMU's location to the radian distance, along the same heading, through the location of the inefficient ADMU to the efficient frontier These are the thin blue lines shown as $\overline{OF}$ and $\overline{OF'}$ in Figures 4-1 and 4-2 above.

Table 4-25. Descriptor for Determining the Input-Oriented TE of Each ADMU, F_{DMU07}

Unique Binary Identifier for this Descriptor	Unique Binary Identifier for the Transformation Function Involved	Input 1	Input 2	Input 3	State

00010001	10010000	Value of the First Factor of production	Value of the Second Factor of production	Current Value of the Production Function	State of the Transformation Function described below.

In the CAPEM simulation the command “to show-tech-efficiency” executes this transformation function. Recall that the factors of production are the inputs to the production function for each ADMU. For the two-dimensional CAPEM PPS they are the inputs that define the x and y axes. The state of this mechanism is the value of the technical efficiency of each ADMU.

4.2.8 Changes in Productive Technical Efficiency over Time

Movement of ADMU in CAPEM represents the change of DEA technical efficiency over time. These changes are the result of decision-making by the ADMUs, that is, the cumulative effect of the rules of flocking and the rules of physics represented by the scenario production function. As with all aspects of the model, each of these rules is embodied in the descriptors of a component mechanism listed in the ccl. At each increment of time all mechanisms and all component mechanism are executed, meaning that each ADMU in the model will make decisions and change (move) or not change at each increment of time. Note that movement of ADMUs may occur whether or not new inputs are received. In the absence of new inputs the ADMU will continue to act on the information it already has. The power of this notation is that each decision made by each ADMU in the model can be informed by the entire CGP at any instance in time. Any component of the model is able to interact dynamically with any component of the model that it can perceive. In this way, all ADMU decisions take into account the behaviors of any and all other ADMUs in the management system. Collective behaviors become non-linear and patterns emerge. By this means CAPEM achieves the ability to differentiate between expected computational results and results that emerge from the non-linear behaviors of populations of autonomous ADMUs.

4.2.9 Implementation of the DEA Production Function

The production function as described by Cooper, Sieford and Tone (2007) defines the optimum relationships between system inputs and outputs. The generic production function in CAPEM is currently assumed to be an equally weighted, constant returns to scale, Cobb and Douglas (1928) formulation (i.e. $Q_{power} = \mathrm{A}(L_{labor}^{0.1})(K_{capital}^{0.25})(F_{fuel}^{0.7})$. This weighting means, in essence, that changes to one output is equivalent to changes in another outputs with respect to inputs (or the converse for the output-oriented model).

Table 4-26. Descriptor for Determining the Value of the DEA PF for each ADMU, F_{FLK02}

Unique Binary Identifier for this Descriptor	Unique Binary Identifier for the Transformation Function Involved	Input 1	Input 2	Input 3	State
00010010	10010001	Alpha – the value of the Cobb-Douglas exponent for the first factor of production	Beta – the value of the Cobb-Douglas exponent for the second factor of production	Value of the constant in the Cobb-Douglas form of the production function	State of the Transformation Function described below.

The simulation command that calculates and provides the value of the maximum output production for each ADMU at each increment of time is “to-report production-function”. The Cobb-Douglas formulation is implemented directly in the simulation code. Alpha and Beta are set by the experimenter at the start of each simulation run.

Use of the generic DEA PF, specifies algebraically, that the PPS has linear topology (invariant under transformations). To specify otherwise would require the introduction of an alternate parametric form of explicitly relating inputs and outputs. Alternatively, as in the power plant example, a validated PF is already available providing validated relationship between inputs and output for use in this research. For the power plant example the relationship can be understood to be, for example:

$$Q_{power} = \mathrm{A}(L_{labor}^{0.1})\left(K_{capital}^{0.25}\right)\left(F_{fuel}^{0.7}\right)$$

Implementation of this relationship imposes additional constraints on the ability of ADMU to make decisions and additional rules being implemented within each ADMU in CAPEM.

Recall that the PF produces an optimum result for production output (Q_{power}). In reality an ADMU would seldom normally be able to achieve this optimum in a single increment of time due to its own existing, de facto inefficiencies and the limitations of its ability to adapt in any single increment of time. CAPEM utilizes this value as a check on feasibility of the rules of flocking made by each ADMU at each increment of time. A flocking-only decision that stays within the optimum values of inputs and output for that ADMU would be unchanged. A decision that exceeds any of the values for input or output of the PF is limited to the flocking decision that uses as its parameters the constrained input or output value. The state of this mechanism is the value of Maximum Production Output.

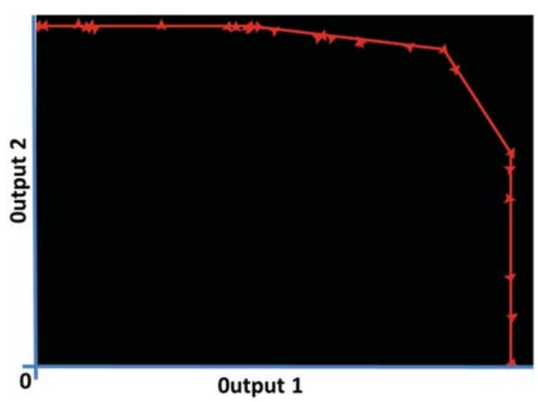
4.2.9.1 Achieving Optimum Management System Technical Efficiency

Economic theory as described by Cooper, Sieford and Tone (2007) assumes that management systems act to maximize efficiency of the system as a whole.

Maximizing system-wide efficiency in CAPEM is synonymous with all ADMUs reaching the DEA EF. A static EF represents an assumption that the goal of this population of ADMUs can be set at the outset of operations and does not need to change. Dynamic maximum efficiency would represent concepts of local and global maximum efficiency found in an uneven fitness landscape (Lewin, 1999). For scoping purposes this research assumes a static EF and flat fitness landscape. Figure 4-2, below illustrates the result of the population of ADMU all achieving their goal and stopping.

A dynamic EF is readily computable in CAPEM at each increment of time but is out of scope of this exploratory research. The concepts of learning described by (Holland, 1995), re-baseline of goals described by (Lee, 2004) and hill-climbing through a fitness landscape described by (Vaneman and Triantis, 2007) are all powerful concepts that would be well represented by CAS ABM. Incorporating them into CAPEM and determining their effects on emergent behaviors of productive efficiency is left to future research.

Figure 4-2. Stopping at the Efficient Frontier



The current CAPEM model therefore incorporates the use of a stopping rule for the movement of individual ADMUs. This rule is executed when movement of an inefficient ADMU in any increment of time intersects the EF. Movement of the

ADMU is halted at the EF. When the ADMU stops in CAPEM, it changes state from inefficient to efficient and is no longer included in the calculation of any of the flocking rules in any future increment of time.

Table 4-27. Descriptor for the Stopping Rule for Inefficient ADMU as it Reaches the Efficient Frontier, F_{DMU02}

Unique Binary Identifier for this Descriptor	Unique Binary Identifier for the Transformation Function Involved	Input 1	Input 2	Input 3	Input 4
00010011	10010010	x-coordinate of ADMU	y-coordinate of ADMU	x-coordinate of first sorted-EF	y-coordinate of first sorted-EF
		Input 5	**Blank**	**Blank**	**State**
		Slope of first sorted-EF line segment			State of the Transformation Function described below.

The simulation code that implements this function is the command “to-report intersect-ef [*x*, *y*]”. The simulation precisely compares the location of the ADMU with the coordinates of the EF at the point of intersection. If the coordinates match the state is true and the ADMU has reached the EF. If the coordinates do not match the state is false and the ADMU continues to move to reach the EF.

4.3 Summary – Applying the Language of Emergence to CAPEM

This research begins to bridge the heretofore separate disciplines of DEA productive efficiency analysis and complex adaptive systems thinking. It identifies and fuses the key building blocks of these two disciplines into a single methodology that provides value to both disciplines. From standard DEA we maintain the basic constructs of productive efficiency: outputs and inputs, DMUs, peer and reference sets, the production function, the efficient frontier, and the definition of technical efficiency. From DPEM, CAPEM adopts the dynamic forms of production, employing the concepts of the closed dynamic system and analysis of system behaviors. Use of the validated CAS metaphor of flocking provided a stable pillar for the building of this bridge between DEA and CAS. It also precluded the need to develop an entirely new approach to the study of risk avoidance and goal achievement in management systems simply for the purposes of this research. The metaphor is at times stretched to its limits for purposes of this exploratory research. Through this research the ability DEA to analyze complex adaptive systems is extended. This research establishes a heretofore non-existent notational framework for representing and analyzing the emergence of patterns of productive efficiency. It is expected that this initial framework can aid continued research to better enable the decision-maker in the actual decision making process and in better describing the actual patterns of productions seen in real world practice.

5 CAPEM Case Study – Deregulated Power Plants

5.1 Objective

The objective of this chapter is to provide efficiency measurement and policy insights derived from an illustrative case study of electric power plants when applying the complex adaptive systems (CAS) flocking metaphor. These measurements and insights are based on the CAS Agent-Based Modeling (ABM) framework developed by Dougherty, Ambler and Triantis (2014a and b) that uses the flocking factors of alignment, cohesion, and separation along with building blocks of the Data Envelopment Analysis form of efficiency analysis. The contribution of this research lies in obtaining an initial understanding of the notion of emergence in the context of production when both “flocking” and productive efficiency principles are considered. From a practitioner’s point of view, the approach allows for the investigation of policies when the achievement of mutual protection/risk reduction (“alignment”) and the achievement of technical efficiency in the least amount of time (“cohere”) are important considerations.

This study uses data for eighty-two electric power plants provided by Rungsuriyawiboon and Stefanou (2003). A series of experiments have been designed to focus on testing the following hypotheses:

Hypothesis 1: The level of adaptability to each of the factors of flocking over time significantly affects the ability of the collective management system to achieve maximum population mean TE.

Hypothesis 2: The level of adaptability to a combination of the factors of flocking over time significantly affects the ability of the collective management system to achieve maximum population mean TE.

Hypothesis 3: The level of adaptability to each of the factors of flocking over time significantly affects the ability of the collective management system to achieve maximum population mean TTEF.

Hypothesis 4: The level of adaptability to a combination of the factors of flocking over time significantly affects the ability of the collective management system to achieve maximum population mean TTEF.

As will be explained in more detail below, measures of population mean technical efficiency (PopMeanTE) and mean time to the efficient frontier (PopMeanTTEF) were chosen as those of that in our opinion would be of most interest to decisionmakers in the experimental scenario. At the same time, these measures can be employed to provide statistical insight into the pattern of flocking behaviors demonstrated by the population of power plants in this experimental scenario.

5.2 Background and Context

There is a growing literature that explores the concepts of dynamic efficiency for production systems. Fallah, Triantis and Johnson (2014) provide an overview of this literature for the non-parametric case. Within the context of this literature, it is assumed that the decision-making units are independent of one another, do not interact or learn from one another and are driven top-down by control-theory based mechanisms. An alternative concept of dynamic efficiency is explored using a CAS ABM paradigm in which the assumption of independence is maintained but at the same time accounts for the multitude of interactions among the decision making units, where dynamic behavior is driven bottom-up by rules embedded in each of the decision-making units.

When considering large organizations with numerous similar production or service entities (e.g., the American Red Cross chapters, brand name healthcare clinic systems, brand name franchises, etc.) the various components that comprise the larger management system are most often labeled or categorized as autonomous but not truly independent in the mathematical or statistical sense. There is often a significant element of top-down control. Such organizations are dependent on factors in their defined environment and are driven by goals and constraints outside themselves. Often unaccounted for however, in existing top-down analytic approaches are the many lower level bottom-up decisions made by the individual chapters, clinics or franchises themselves, that are a primary driver of the dynamic behavior of the system. These lower level decisions are represented by the agent-based rules which are described in chapter 3 as a building block of CAS ADM. For example, an "independent" franchise pays the corporate organization an agreed upon amount of money for the franchise, displays the logo in accordance with agreed upon rules, adheres to a common set of accounting rules and methods of making or distributing the product (i.e., food, cosmetics, lawn care). Outside these constraints the individual components have a vast array of local choices about the physical layout of a store, how much they will pay employees, how much time they spend training employees, what specials they offer and within certain parameters, how much they charge locally for the product or service (Coudreit, 2014).

This autonomy is well represented in the CAS ABM paradigm, to the degree that the components of the management system, individual power plants, when properly isolated from the top-down controls, can be considered to be independent for purposes of statistical analysis. Factors exogenous to the individual components of the management system, the power plant ADMUs, are represented in the CAS ABM environment which itself is a closed system. This independence is enforced in three important ways. First, even though, as previously described, individual CAS ABM agents are themselves semi-open systems, they control what information crosses their own boundaries from their environment. ADMUs (i.e., franchises, power plants) make their own choices about what information they accept as inputs. This is like having the ability to choose which form of chapter, clinic, or brand of franchise to they wish to associate with. In the power plant case study individual power plants choose what information they accept from the environment such as the minimum and maximum limits of the environment and the desired standard of performance, represented by the location of the common efficient frontier.

Second, as has been have described previously, in Chapter 3, each component has its own internal rules which continue to seek to achieve its own goals, adapt and act on others as it chooses regardless of what new inputs are provided by the environment or other ADMUs. CAS ABM components can function whether or not new inputs are provided at all. Continuing the illustration, the franchise decides for itself what it pays local employees, how it trains them, how many employees to have, how many to have on a shift at any one time, when to open and close. In the power plant case study, individual power plants would continue to seek increased technical efficiency and produce electrical power even if some or all other power plants disappeared from the simulation.

Third, these entities choose what other entities to interact with locally to gain information and achieve their goals. As autonomous franchises they decide, for example, where they buy their meat, their vegetables, what industry or civic associations they belong to and which waste management-company to use. They decide which other franchises in the same brand are similar enough to themselves that they continuously observe them for changes in prices, approach to local advertisements and for ideas on employee recruiting practices. In the power plant case study individual ADMUs decide for themselves which of its neighbors to observe as “flockmates” or peers and which neighbors they chose to influenced them. When aligning ADMUs may use any sub-set or the entire population of inefficient ADMUs. When they cohere they choose only the two nearest efficient ADMUs or a combination of the efficient ADM. Each entity makes its own decisions given a common environment, its own choice of inputs (resources), and its internal rules and chooses for itself what other local entities it interacts with. In contrast to linear optimization-based approaches (Charnes, Cooper and Rhodes, 1978) and in contrast even to non-linear, control-theory approaches (Vaneman and Triantis, 2007) associated with the measurement of productive efficiency, complexity science-based approaches allow for interaction among components and meet the level of precision necessary to conform to the statistical definition of independence. This has deep ramifications for understanding dynamic behavior, the measurement of dynamic performance of the DMUs and the kind of insights that can be gained from the use of CAS ABM.

ADMU interactions and their impact on efficiency performance has been accounted for as previously described in Chapter 2, by adapting the CAS convention of using ecosystem metaphors, specifically the CAS ABM “flocking” metaphor as defined by Reynolds (1987). Dougherty, Ambler and Triantis (2014a) discuss the conceptual linkages associated with the mapping of the building blocks of the flocking metaphor, with the building blocks of productive efficiency along with their associated inferences to the world of de-regulated power plants. In Dougherty, Ambler and Triantis (2014b), CAPEM is mathematically expressed using the CGP notation (Holland, 1999) and describe the implementation of CAPEM a CAS ABM simulation, NetLogo platform using formulations implemented by Wilensky (1999).

5.3 Extending DEA into a Complex Adaptive Systems Theory-Based Approach

In this chapter, an illustration of the use the CAPEM approach is provided using a case study of electric power generation. The use of an electrical power plant case study as an illustration of productive efficiency concepts is not new. Vaneman and Triantis (2007) provide a system dynamics approach to the measurement of dynamic productive efficiency of power plants employing data from the Kopp (1981) study. No attempt is made in this research to infer a direct comparison with Vaneman and Triantis (2007), using this subject area (fuel-based production of electrical power) provides a well-defined production technology and is expected to enable useful comparisons in future research.

Färe and Grosskopf (2000) provide a previous study exploring the concept of dynamic efficiency for production systems. Their Dynamic Data Envelopment Analysis (DDEA) approach computes a series of simultaneous linear equations at designated points over time, employing the result of the computation at each point as inputs or starting conditions for computations at the next increment of time. The later approach by Vaneman and Triantis (2007), known as the Dynamic Productive

Efficiency Method (DPEM) explores the concept of dynamic efficiency for production systems, as mentioned above, using a control-theory based SDM based approach to determining dynamic efficiency behavior. Both approaches assume independence of the DMUs and a well-defined production technology as the means of driving system behaviors. CAPEM extends the study of dynamic efficiency for production systems by replacing the top-down driven behaviors with bottom-up CAS ABM behaviors and replacing the physics-based definition of the production technology with the biologically-based flocking metaphor as the means of driving system behavior. In this research, interactions among autonomous or self-governing entities guided by their own internal rules, drive system behavior. The physics that defines the relationship among the inputs and outputs (i.e., fuel, labor and electrical production) is represented in CAPEM but it is used only to calculate or account for the total electricity produced by the system and is no longer used as the driver of system behavior. In this case study scenario decisions-makers who employ CAPEM have accepted the notion that the bottom-up ecosystem metaphor (alignment, cohesion, separation) are the way to determine policy changes (i.e., changes in the use of fuel and labor) and make decisions about their productive efficiency. In this manner CAPEM extends DEA from an approach defined by the physical relationships between fuel, labor and electricity to an approach defined by the ecosystem of relationships among the decision-makers, the world of complexity science and CAS ABM methods.

5.3.1 An Analysis of Both Individual and Collective Decision-Making

In standard DEA and DDEA (Färe and Grosskopf, 2000) it is assumed that decision-makers within each power plant have sufficient insight to make decisions about their own use of the factors of production at each increment of time. They however have no means of anticipating or leveraging a pattern of decisions made by other power plants over time. There is no notion of collective, coordinated decision-making or coordinated motion among DMUs and no means of representing it. In DPEM (Vaneman and Triantis, 2007), the system dynamics model, reinforcing and balancing loops were designed to represent the dynamic behaviors of the physical laws embedded in the model. Over time a single power plant employing this production technology employs the factors of production and responds to the top down controls designed into the model in an effort to optimize the utilization of inputs and/or the production of outputs and achieve a state of theoretically optimum equilibrium for each DMU. The main outcome of the DPEM is a determination of the optimal path to the production goal that is provided a priori by a single decision maker. This is a desirable and valuable result of using the top-down physics based approach. The two approaches need not be seen contradictory or in competition with one another. They can be complimentary with each approach offering insights not provided by the other. CAPEM is by definition, is limited to an analysis of a single decision-maker. Its strength is that it accounts for the ability of decision-makers to learn from one another and adapt based on the experience of the other decision-makers.

One known attempt made to consider influences of multiple DMUs on one another in a system dynamics model was made recently by Fallah-Fini, Triantis, Rahmandad and de la Garza (2014). In this study multiple power plants modeled individually and operating simultaneously sought to consider the non-linear effects on the change in productive efficiency overtime. The change in the physical factors of production from each DMU were combined and their effects on the total production of electricity was analyzed. Their individual and collective behavior remained however under the control of a common top-down control mechanism as all individual DMUs sought a collective optimum. This contrasts markedly to the

CAS ABM approach where collective behaviors emerge bottom-up from the internal, independent aspects of ADMU decision-making. The two forms of analysis, systems dynamics modeling and CAS ABM may, in fact, be complimentary, each providing valid, yet different insights. Further comparisons to Fallah-Fini, Triantis, Rahmandad and de la Garza (2014) are left to future research.

CAPEM enables representation of the components of the management system and the interactions among them thus, CAPEM represents both the individual and collective behaviors of the system. An accounting is made of the influence of the individual power plants on the decisions made by all other power plants in the population, in each increment of time. The goal of the individual power plant remains the same as in standard DEA (Cooper, Sieford and Tone, 2007) and DPEM (Vaneman and Triantis, 2007), that is, optimizing its own use of inputs while maintaining the desired level of electrical power production. In CAPEM, by definition, the collective behavior of a population of independent power plants results in a form of collective behavior representative of a larger deliberate or de facto management system and becomes significant in understanding the results of the experiment described subsequently. Because each power plant is autonomous however, analysis of the decision-making of individual power plants can be achieved as well.

5.3.2 Electric Power Generation Data and the Production Technology

To produce electricity (Q) in oil-fired power plants capital (K) is invested to build and maintain the physical plant. Fuel (F), in the form of oil is burned and laborers (L) are employed to operate the plant. In this research just as in Koop (1981) and Vaneman and Triantis (2007) productive efficiency of plants that transform capital, fuel and labor into electric power is again examined. Empirical data published by the Rungsuriyawiboon and Stefanou (2003) study of 82 deregulated US oil-fired power plants over a period of 14 years is employed.

The power plant technology, represented by the relationship between the physical factors of production (capital, fuel and labor), as described by a Cobb-Douglas (1928) production function for these three inputs and a single output (electrical energy) is assumed. The production function used in the Rungsuriyawiboon and Stefanou (2003) study and in this research case study takes the form of $Q=0.049(L^{0.1})(K^{0.25})(F^{0.7})$. Capital is assumed to be fixed. The value of K in this equation becomes equal to 1 for the experiment. In essence this is not considered as a factor for which decisions are made. Only the effects of the change of fuel and labor on the production of electricity are considered. Further, the assumption of a constant returns to scale technology is made, meaning that if all inputs increase by a certain percentage (i.e, 5%) then the output increases by the same percentage (i.e., 5%).

5.4 PowerCorp - Analysis of Electric Power Generation Using CAPEM

In this scenario the management system is composed of 30 deregulated US electric power plants selected from the Rungsuriyawiboon and Stefanou (2003) study data. This assumed management system is given the name PowerCorp. In this scenario the senior management of PowerCorp has chosen to test an ecosystem-like, complex adaptive approach to corporate decision-making. By envisioning themselves as an ecosystem, PowerCorp is choosing a policy of localized, leaderless decision-making by independent power plants. By applying the validated CAS emergent behaviors inherent in the flocking metaphor PowerCorp has chosen a collective corporate policy of “coordinated motion among multiple autonomous agents” (Dougherty, Ambler, and Triantis, 2014a). The internal rules that define individual power plant behavior in this scenario are those defined and validated by

Reynolds (1987). The autonomous agents in this scenario are the individual power plants. Coordinated motion in this scenario is achieved by a PowerCorp corporatewide policy of fully open communication among power plants sharing its current TE and the policy of TE it plans to pursue in the next increment of time (monthly). The choices available to the decision-makers in each of these fully informed autonomous power plants (i.e., to align, cohere or separate), determine the ability of PowerCorp to achieve its goal of continuously increasing technical efficiency.

The simulation platform and code used to implement these behaviors is a modified version of flocking model found in the NetLogo model library (Wilensky (1999). In this scenario each individual power plant seeks to maximize the level of electricity produced while minimizing the level of inputs of fuel and labor used to do so. Note that there is no single PowerCorp decision-maker. PowerCorp under these conditions becomes only the environment in which the power plants operate. PowerCorp maintains global conditions and global information but exercise no decision-making abilities. Using the CAPEM simulation and playing the role of analyst for PowerCorp this researcher experiments with a full range and combination of available choices to determine the combination of parameters for alignment, cohesion and separation that most often achieves the best corporate-wide results. This experiment is performed to determine if simulation based experimentation employing the CAS ABM flocking metaphor can provide PowerCorp with useful insights and options for achieving increased productive TE in the least possible time.

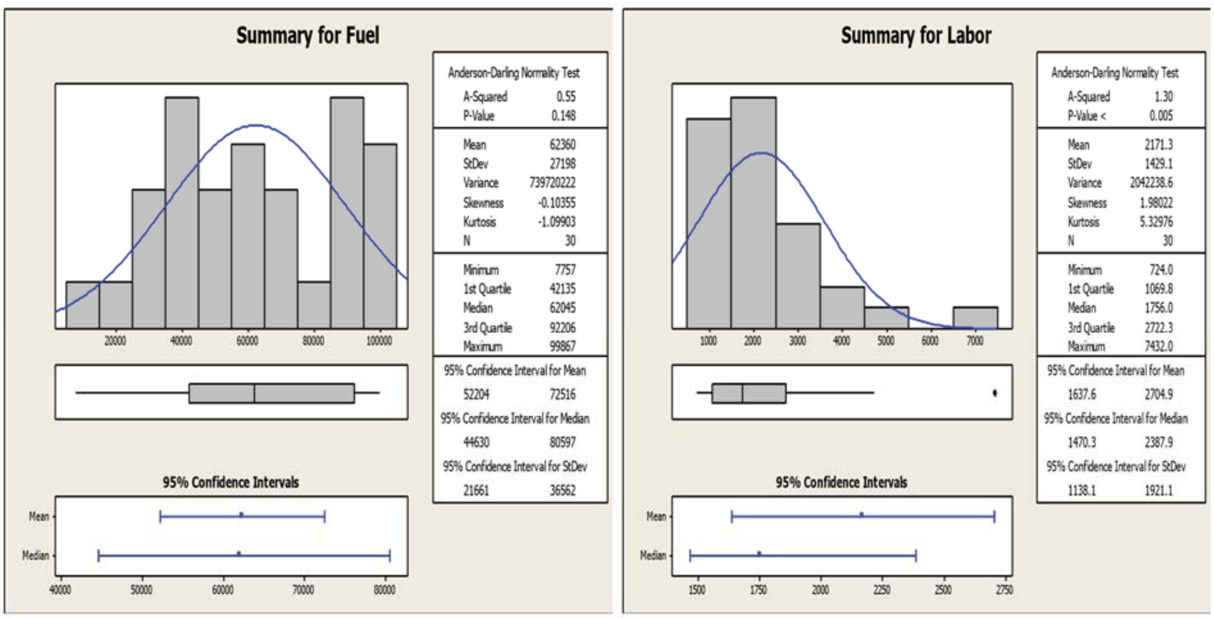
5.4.1 Initial Conditions

Figure 5-1 below provides a summary of the values for the level of fuel and labor used as inputs and the level of electricity produced by the population of 30 ADMUs selected from the data for this simulation based experimentation. The initial 30

ADMUs selected for this experiment were chosen in such a way that their operating conditions were most similar both in terms of the fuel and labor consumption.

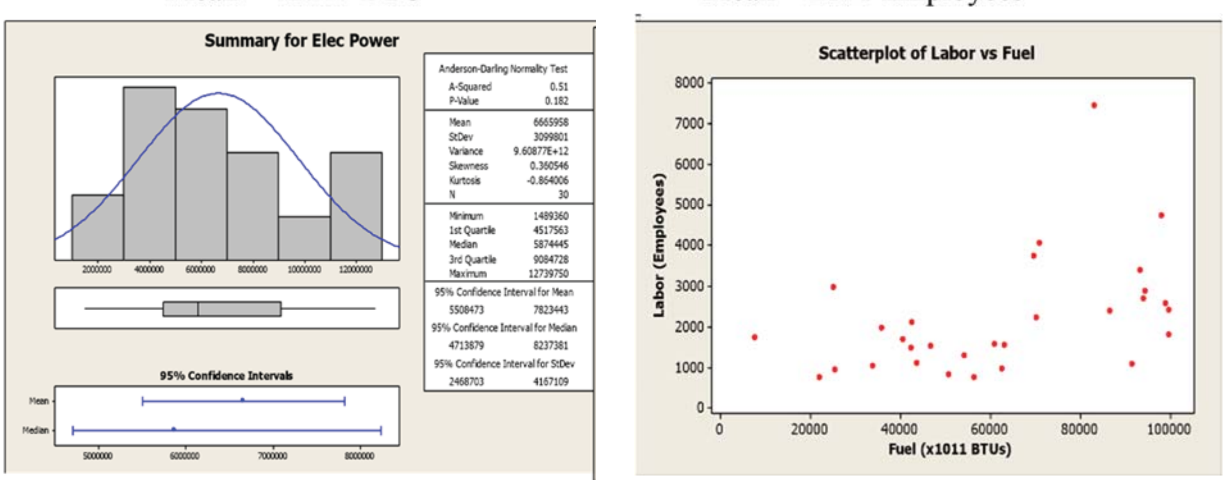
The range of fuel and labor inputs in the full population of 82 power plants was quite extreme. To simplify this analysis and facilitate clearer illustration of the case study the population is reduced to the 30 power plants closest to the origin and with the least collective variability. Analysis of the larger population and the identified outliers and their effect on productive efficiency will be left to future research.

Figure 5-1. Summary of the Initial Conditions of the Thirty Power Plants



Mean = 62360 BTU

Mean = 2171 Employees

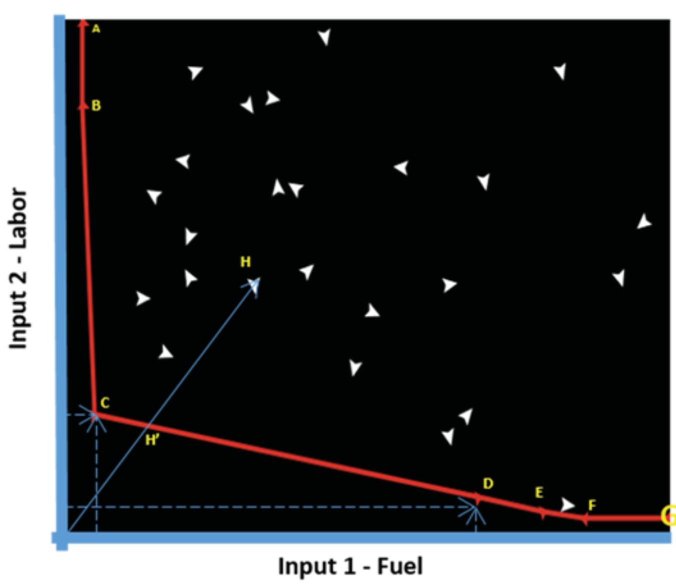


Mean = 6,665,968 Megawatt Hours

5.4.2 The PowerCorp Environment

The CAS ABM agent environment representing the productive possibility space (PPS) has been implemented, as described previously by Dougherty, Ambler and Triantis (2014b), and is shown in Figure 5-2, below as a two dimensional space defined by the axes representing two of the PowerCorp input factors of production (i.e., fuel and labor). Output (electrical production) is not displayed but is calculated and captured in the output files of each experiment. The individual power plant's initial location is displayed as an initial scatter of white arrowheads in the PPS coordinate space. The initial locations for each of these 30 selected power plants is defined by the empirical data from the year 1986 data taken from the Rungsuriyawiboon and Stefanou (2003) study.

Figure 5-2. CAPEM NetLogo Display of the PowerCorp Management System PPS



The red piecewise linear curve within the PPS represents the DEA efficient frontier (EF). An innovation developed in the conduct of this research was the manner of defining the EF in CAPEM. Using basic trigonometry the CAPEM code finds the most extreme values of the inputs, in effect identifying the most efficient DMUs. By connecting the most efficient DMUs in the first increment of simulated time the piecewise linear curve is formed, emulating the standard DEA approach of benchmarking efficiency. The power plants that are identified in the initial time increment of the simulation as efficient are those to which the less efficient DMUs cohere throughout the experiment. As DMU seek to continuously increase technical efficiency over time they achieve maximum possible efficiency which in the CAPEM display of the PPS is the EF. Within this environment each power plant can sense the location (use of inputs) of its neighboring power plants and can sense their heading (the change in technical efficiency in the current increment of time) of all or a selected sub-set of the other power plants. TE of an individual ADMU defined as the proportion of the chord lengths OH'/OH is indicated in this figure by the thin blue line extending from the origin. The TE of ADMU H, for example, is measured by the radial distance from the origin to the ADMU divided by the radial distance between the origin and H'. The CAS ABM environment and the component power plants represented in this figure constitute, for purposes of this scenario, the CAPEM PowerCorp management system.

5.4.3 Implementing Individual Power Plant and PowerCorp Goals (Percepts and Actions)

Recall that percepts are the CAS ABM mechanism for selecting the information s it employs to make decisions and that actions are the choices made by the ADMU of what information it will share with the environment or other ADMUs. Recall also that the goal of each power plant in this scenario is to minimize the level of inputs used by a power plant to produce a desired level of output. As a step in the initialization of the CAS ABM simulation the most efficient power plants in the population (the DEA peer set) are perceived and used to define and display the efficient frontier (EF). Each power plant in the corporation is able to perceive the identity and location of those power plants that constitute the EF and distinguish them from the other less efficient power plants. The EF becomes the benchmark for less efficient power plants to judge their own relative level of efficiency and make independent choices about the level of inputs they wish to use in each subsequent increment of time. At the end of each simulated increment of time each power plant acts on its environment by selectively reporting its current use of fuel and labor and contributes to the corporate management system by influencing the next location and heading of other ADMU that have selected it as a neighbor.

5.4.4 Implementing Power Plant Rules and Interactions

In the interest of simplifying and scoping this research all power plants have been assigned the same internal rules and define their interactions in the same way. While this is not a CAS ABM constraint, distinctions among ADMU have been intentionally limited to two types and four characteristics. The two types are those ADMU that are efficient and those that are less efficient power plants. The first type are the power plants that achieve a location on the EF, these power plants have improved from a less efficient to an efficient state combination of inputs and outputs. Once an ADMU achieves a technical efficiency score of 1.0, it is by definition on the EF and remains at the same location on the EF throughout the remainder of the simulation. The power plants that become efficient (i.e., reaches the EF) are no longer perceived by the remaining less efficient power plants for purposes of alignment or separation. By definition, efficient power plants are considered for purposes of cohesion which, as described previously, is movement toward the DEA peer set or the movement toward the power plants on the EF that are closet to them in terms of distance.

For purposes of understanding alignment, the definition of CAS ABM neighbors leveraged the standard DEA definition and therefore included all remaining less efficient power plants as members of the DEA reference set (Cooper, Sieford, and Tone, 2007). Some implementations of flocking restrict the number of neighbors to a smaller subset of the nearest 5 or 7 other ADMUs. For purposes of implementation of cohesion Dougherty, Ambler and Triantis (2014b) employs as neighbors the two nearest efficient power plants, consistent with both the flocking metaphor and the standard DEA approach for selection of its peers.

5.4.5 The Flocking Variables

After running numerous exploratory excursions of the simulation and examining the change in the values of the flocking variables (maximum alignment, cohesion and separation turn and minimum separation distance) it was noted that there was little change in the effects of the variables beyond a maximum of 25 degrees., It was determined therefore that the range of variability among the flocking variables for purposes of this model and research should be in a range of from 0 to 25 degrees. The lower bound (0 degrees) is analogous, in the real-world, to a power plant that is unable to makes changes or adapt to the desired management policy at each increment of time. The upper bound (25 degrees) is analogous to the power plant having a high degree of adaptability to the desired management policy during each increment of time. The use of the lower bound effectively eliminates a flocking variable as a factor that influences other power plants. Conversely, to isolate a single factor, cohesion for example, as the determinate of power plant behavior, the other variables may be set at zero. Through experimentation it was determined that a variable setting beyond 25 degrees for any of the flocking variables resulted in little to no additional significant change in the level of productive efficiency achieved by a power plant. Experimentation indicates that an ADMU seldom, if ever, needs to turn (adapt) more than 25 degrees to achieve the next desired policy decision per increment of simulation time (i.e., a NetLogo tick).

5.4.6 Measuring Time and Distance

The Rungsuriyawiboon and Stefanou (2003) study provided data for annual levels of the factors of production, for a period of 14 years. The simulation increments of time were specified at two levels of granularity deeper (weekly) and the minimum time horizon for the experiment was therefore set at 672 increments or NetLogo ticks (14 years x 12 months x 4weeks). In an effort to economize on the length of time needed to run the required number of excursions and after some initial experimentation, It was determined through preliminary experimentation that all meaningful results occurred before 1344 ticks (672 x 2) increments of time. Rounding up to 1500 ticks as the upper limit of time provided reasonable confidence of having a sufficient sample for capturing the mean population mean. If 1500 was assumed to be equal to the 14 year span of the Rungsuriyawiboon and Stefanou (2003) study data, each increment of time in the simulation would have a value of 2.232 weeks (1500/(14 years x 12 months x 4 weeks)) or 0.558 months (2.232 weeks/4 weeks/month). We have observed in our recent analyses that the patterns of behavior in each excursion are fully evident within 900 increments of time. In future research we will consider further reducing the maximum necessary time horizon to be 900 increments of time and still retain a reasonable level of confidence of capturing a good sample for determining the population mean.

Defining and measuring distance in the simulation allows me to define and measure the velocities and acceleration of changes in technical efficiency of the power plants under a range of conditions and consequently test the hypotheses.

Measuring distance is essential in defining the interaction between a power plant and its nearest neighbor for purposes of the rules of flocking. The NetLogo simulation measures distance in patches, a rectangle measured in pixels in the NetLogo display. The size of each patch can be scaled to accommodate the desired limits of the NetLogo environment (the PPS) to accommodate the desired increments along the axis. The size and scale of the environment is set manually in the simulation settings by specifying a minimum x (min-pxcor) and a minimum y (min-pycor) coordinate and by specifying a maximum x (max-pxcor) and a maximum y (max-pycor) coordinate. Consistent with standard DEA practice the min-pxcor and min-pycor are the origin (i.e., (0,0) of the coordinate scale). Given the maximum known values from the data, each axes was scaled accordingly. For the use of fuel, the maximum value was 984,487 BTU. The maximum value of the x-axis was therefore set at 1,000,000 with each of 10 increments of the x-axis to represent 100,000 BTUs of fuel. Similarly, given the maximum value for the use of labor in the data of 29,448 employees, the y-axis was set to a maximum value of 30,000 with each increment on the axis to representing 3000 employees. After considerable initial testing, the use of these increments proved sufficient.

5.5 Elements of Analysis

5.5.1 Elements of Analysis for Individual Power Plants

A complete set of CAPEM excursions for this experiment consists of the population of 30 ADMUs making decisions over a period of 1500 increments in time across 1296 runs (excursions) of the experiment covering all combinations of the four flocking factors (alignment turn, cohesion turn, separation turn and separation distance) run at each of the six possible levels of adaptability previously discussed (i.e., 0,5,10,15,20,25). From each of the 1296 CAPEM excursions the following data for each individual ADMU was captured:

- Levels of input for fuel and labor for each ADMU, at each increment of time in all 1296 runs
- Levels of output for the production of electrical power for each ADMU, at each increment of time in all 1296 runs
- Technical Efficiency (TE) of each ADMU, at each increment of time in all 1296 runs
- Mean Technical Efficiency (MeanTE) for each power plant, for the period of the simulation excursion (MeanTE) in all 1296 runs
- Mean Time to Achieve the Efficient Frontier (MeanTTEF) for each ADMU, for the period of the simulation excursion in all 1296 runs

For each excursion output files captured data containing contextual information including the version of the CAPEM code and the dimensions of the NetLogo environment (the PPS). This environment is known in NetLogo as the "World." Also included in this information are the run (excursion) number and the level of adaptability (0,5,10,15,20,25) of each of the flocking factors. Finally, included in this context information are the constant and the exponents of the factors of production (fuel and labor) that define the production function (PF).

5.5.2 Elements of Analysis for the Collective Management System

For purposes of this experiment two of the many possible estimators of collective management system behavior that the PowerCorp decision-makers might use to monitor the progress of their population of power plants as they seek continuous improvements in technical efficiency were chosen. To test the experimental hypotheses, described below, across the 1296 CAPEM excursions, the following estimators for collective behavior were calculated and compared for each excursion:

- Mean TE for the population of 30 power plants for the period of an excursion (PoPMeanTE)
- Mean time for the population of 30 power plants to reach the DEA efficient frontier (PoPMeanTTEF)

To determine the PoPMeanTE a mean TE was computed for each DMU in a single excursion of the experiment and then the mean of these individual means was determined. PopMeanTE is therefore an aggregate estimate for the technical efficiency of the whole population of 30 PowerCorp power plants in each excursion of the 1296 possible combinations of levels of adaptability for each of the 4 flocking factors. Both the variable name (PopMeanTE) and this short description of population mean TE will be used throughout the chapter, sometimes together, depending on the need for brevity and or added clarity.

PoPMeanTTEF is determined in the same manner as PoPMeanTE and is therefore an aggregate estimate of the mean time for the whole population of 30 PowerCorp power plants to achieve collective maximum efficiency in each excursion of the 1296 possible combinations of levels of adaptability for each of the 4 flocking factors. This is equivalent to saying that all DMUs that can achieve maximum efficiency under a given combination of levels for the four variables will have reached the EF for that excursion.

By capturing data for both the individual DMUs and for the collective management system the analyst is able to examine the experiment at both the individual ADMU level or at the level of the whole population of 30 ADMUs. This research is most interested in the technical efficiency of the management system as a whole. As explained Chapter 3, it is in the analysis of collective interactions among the 30 members of the population that will lead us to discover emergent behaviors, patterns in setting policy that will offer the greatest probability of achieving optimal technical efficiency. We therefore focus this analysis on the data captured for the whole population of 30 ADMUs, PopMeanTE and PopMeanTTEF.

5.6 The Design of the Experiment and Analysis of Variance Hypotheses

5.6.1 Summary of the Design of the Experiment

To conduct a CAS ABM flocking metaphor experiment needed to test both the experimental and Analysis of Variance (ANOVA) hypotheses and to gain insight into the use of the CAS ABM metaphor analysis of productive efficiency the following steps were performed:

Table 5-1. Summary of Experimentation — Power Plant Illustrative Example

Design of the Experiment
• Given: Rungsuriyawiboon and Stefanou (2003) provide data of the annual values for fuel, labor used and energy produced for 82 power plants for the period 1986-1999 (14 years). • Four factors of the CAS flocking metaphor (alignment turn, cohesion turn, separation turn, separation distance); (the first 3 factors are measured in degrees, the last factor is measured in simulation platform segments (patches). • Six desired levels for each of the four factors (0,5,10,15,20,25 degrees or patches). • Population: 30 power plants selected from the Rungsuriyawiboon and Stefanou (2003) data. The 30 power plants chosen from the total population were those with the most similar levels of electrical production and the most similar requirements for fuel and labor. • Together the speed of the NetLogo-based (Wilensky (1999) CAPEM simulation and the ability of the Behavior Space NetLogo add-on application to automatically replicate runs across a full range of values for each variable are able to run 1296 excursions of all six desired levels of all four variables and provide documented results data in less than an hour. • Design: 6^4 Full Factorial – 1296 excursions for each complete experiment. • Replication: 1 – using a single repeated random number seed.
Simulation Platform

• NetLogo-based CAPEM simulation version 0.99 (Gold). • CAPEM Environment (the Production Possibility Space) set with the origin (0,0) in bottom–left of the NetLogo World • The x-axis (fuel) ranges from 0 to a maximum of 1,000,000 BTUs (the maximum value of fuel usage for the 82 power plants from 1986 to 1999 was 984,487). This axis is divided into 100 increments representing 100,000 BTU per increment. • The y-axis (labor) ranges from 0 to a maximum of approximately 30,000 Employees (maximum value for use of labor for the 82 power plants from 1986 to 1999 was 29,448. This axis is divided into 10 increments representing 3000 employees per increment.
Excursions Initialization/Setup
• Data Input File • The initial position of each of the 30 selected power plants in the CAPEM environment is set equal to their 1986 historical values for fuel and labor • Random Number Seed = 300 • DEA Production Function: Constant Return to Scale = 1 • Proportionality/weights of the factors of production, fuel=0.7, labor=0.2 • Efficiency Strategy = Input Minimization • Initial levels of the flocking factors all set to 0 degrees and 0 patches
Base Case
• A standard DEA analysis (DEA Solver) of the Rungsuriyawiboon and Stefanou (2003) data for the values for the historical mean technical efficiency (TE) of the population of the 30 selected power plants.

• Time Horizon: 1500 increments = 20 Years; Increment duration = 2.232 weeks
Excursions
• Excursions from the base case are defined by variations in the four flocking factors, vary alignment, cohesion, separation max turn angles over a range of 0-25 degrees at 5 degree intervals and at the same time vary separation distance over a range of 0-25 increments at 5 increment intervals. • Time Horizon: same as base case
Data Capture

- In the CAPEM simulation runs the following data were captured for each ADMU in each of the 1296 excursions:
- Levels of Input for Fuel and Labor for each ADMU at each increment of time
- Levels of Output for Production of Electrical Power for each ADMU at each increment of time
- Technical Efficiency (TE) of each ADMU at each increment of time
- The mean TE of each power plant for the period of the excursion (Mean TE)
- Time to Achieve the Efficient Frontier (TTEF) for each ADMU for the period of the simulation Derived Data for the sample population of 30 ADMUs for each of the 1296 Excursions:
- Mean TE for the population of power plants for the period of an excursion (PoPMeanTE)
- Mean time for the population of power plants to reach the DEA efficient frontier (PoPMeanTTEF)

Statistical Analysis

- Descriptive statistics of the population of 30 ADMU across the 1296 excursions for:
- Usage of Fuel, Labor Inputs and Electrical Production
- Population Mean Technical Efficiency (PopMeanTE)
- Population Mean Time to the Efficient Frontier (PopMeanTTEF)
- Analysis of Variance (ANOVA) – of the full 6^4 factorial to determine the significance of each of the four flocking factors and each of their interactions
- Analysis of Means (ANOM) – of the full 6^4 factorial to compare and complement the insights gained by the ANOVA Graphical analysis of:
- Main Effect Plots (of the individual flocking factors) for PopMeanTE and PoPMeanTTEF Interaction Plots (of the combination of flocking factors) for PopMeanTE and PoPMeanTTEF Hypothesis Testing:
- Hypothesis 1: The level of adaptability <u>to each</u> of the factors of flocking over time significantly affects the ability of the collective management system to achieve maximum population mean TE.
- Hypothesis 2: The level of adaptability <u>to a combination</u> of the factors of flocking over time significantly affects the ability of the collective management system to achieve maximum population mean TE.
- Hypothesis 3: The level of adaptability <u>to each</u> of the factors of flocking over time significantly affects the ability of the collective management system to achieve maximum population mean TTEF.
- Hypothesis 4: The level of adaptability <u>to a combination</u> of the factors of flocking over time significantly affects the ability of the collective management system to achieve maximum population mean TTEF.
- Two-Way ANOVA to compare the variability of selected pairs of flocking factors enabling us to understand the relative significance of combinations of variables in determining the total variability of the results of the experiment.
- Analysis of the Means, a statistical technique that compliments the ANOVA by analyzing the means of the ANOVA sums of the squares statistic to determine the significance of the effects of each of the variables on one another thus elaborating on the findings and conclusion made by the ANOVA with respect to the hypothesis.

Note that for scoping purposes the experiment was designed with only one excursion for each population under each combination of the six levels for each of the four variables, using a single common random number seed for each excursion. As stated previously this analysis focuses on the collective elements of analysis (i.e., PopMeanTE and PopMeanTTEF) for which, in this experimental design, there are a large number of samples (1296) rather than focus on the estimators of individual behavior (Mean TE, Mean TE for each Power Plant), for which, as just stated, only one excursion was run. To focus on the estimators of individual power plants behavior it would be necessary to have a statistically significant number of excursions for each power plant (i.e., 30) The number of excursions for such an experiment would be prohibitive (1296 x 30). In this research power plants are treated as single data points. It is the estimators of collective behaviors across the range of factors and levels that will provide the desired insight into the behavior of the management system as a whole and is therefore of interest in this design. Analysis of the pattern of behavior for individual power plants is left to future research.

5.6.2 Analysis of Variance Hypotheses

The study hypotheses, section 5.1 above, includes directionality (i.e., the estimators will increase or decrease) as the levels of adaptability increase. Below is a modified statement of the research hypotheses needed to conduct the ANOVA. In contrast to the statement of the study hypotheses the statement of the ANOVA hypotheses addresses a more limited purpose, primarily to determine the significance of the factors. The ANOVA hypotheses intentionally do not include directionality.

- $H1_0$ (null hypothesis): the mean effects of the change in levels of adaptability (i.e.,0,5,10,15,20,25) for each of the four flocking factor (alignment turn, cohesion turn, separation turn and separation distance) on the mean technical efficiency for this population of Power Plants (PopMeanTE), are the same.

Recall that the population mean TE (PopMeanTE) of this population represents the technical efficiency for each excursion of the simulation with each excursion being defined by a combination of four levels of adaptability (i.e., 0,5,10,15), one for each of the four flocking factors. Note also that if the mean of this estimator is the same there is insufficient differentiation among the levels and therefore the null hypothesis cannot be rejected. The effects of the levels on TE in this case are found to be not significant.

- $H1_1$ (alternative hypothesis): the mean effects of the change of levels of adaptability (i.e.,0,5,10,15,20,25) for each flocking factor (alignment turn, cohesion turn, separation turn and separation distance) on the mean TE for the population of Power Plants (PopMeanTE) , are different.

  Note that if the null hypothesis is rejected, the mean effects of the levels of that flocking factor are significant and become valuable to use for setting policies needed to achieve improvement in efficiency.

- $H2_0$: the mean effects of the change of the levels of adaptability (i.e., 0,5,10,15,20,25) for a combination of the flocking factors (alignment turn, cohesion turn, separation turn and separation distance) on the mean TE for the population of Power Plants (PopMeanTE), are the same.
- $H2_1$: the mean effects of the change of the levels of adaptability (i.e., 0,5,10,15,20,25) for a combination of the flocking factors (alignment turn, cohesion turn, separation turn and separation distance) on the mean TE for the population of Power Plants (PopMeanTE), are different.
- $H3_0$: the mean effects of the change of the levels of adaptability (i.e., 0,5,10,15,20,25) for each flocking factor (alignment turn, cohesion turn,

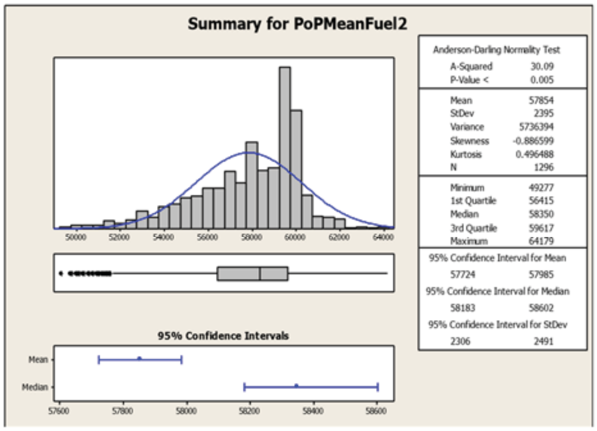
separation turn and separation distance) on the mean time to achieve the efficiency frontier for the population of Power Plants (PopMeanTTEF), are the same.

- $H3_1$: the mean effects of the change of the levels of adaptability (i.e., 0,5,10,15,20,25) for each flocking factor (alignment turn, cohesion turn, separation turn and separation distance) on the mean time to the efficient frontier for the population of Power Plants (PopMeanTTEF), are different.
- $H4_0$: the mean effects of the change of the levels of adaptability (i.e., 0,5,10,15,20,25) for a combination of the flocking factors (alignment turn, cohesion turn, separation turn and separation distance) on the mean TTEF for the population of Power Plants (PopMeanTTEF), are the same.
- $H4_1$: the mean effects of the change of levels of adaptability (i.e., 0,5,10,15,20,25) to a combination of flocking factors (alignment turn, cohesion turn, separation turn and separation distance) on the mean TTEF for the population of Power Plants (PopMeanTTEF), are different.

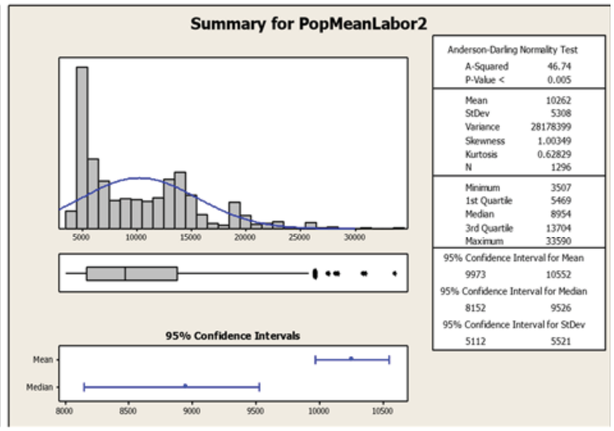
5.7 Simulation Results

Figure 5-3 below, provides a summary of the data captured for the use of fuel and labor inputs and for electricity produced for the population of 30 power plants across a full set of 1296 CAPEM excursions.

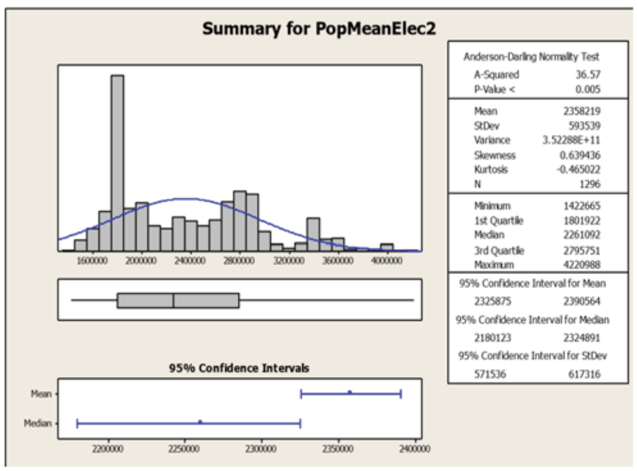
Figure 5-3. Summary Results for Population Mean Fuel, Labor and Electrical Production



Mean = 57,854 BTU



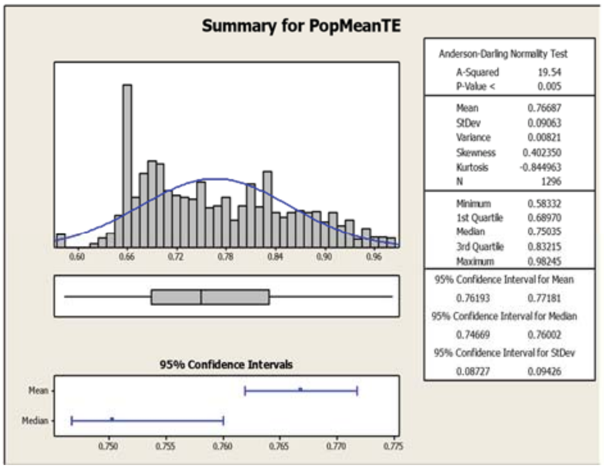
Mean = 10,262 Employees

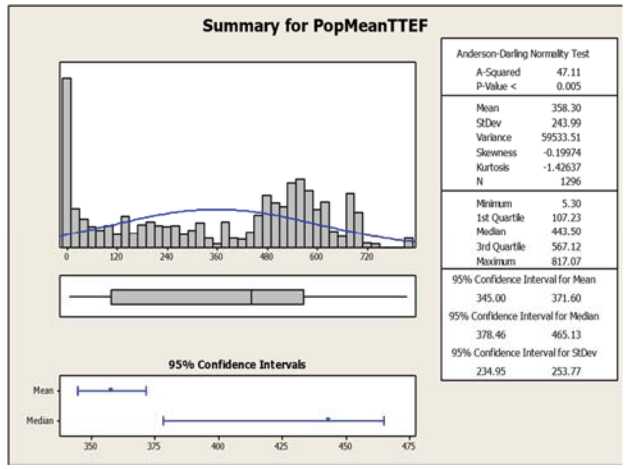


Mean = 2,358,219 Watt Hours

From this set of experiments it is determined that the population of 30 power plants used a mean level of 57,854 BTUs and a mean level of 10,262 Employees to produce a mean level of 2,358,219 watt-hours of electrical power. As shown below, the PopMeanTE for all excursions across all levels of the four flocking factors over the full period of these simulations was 0.76687 and the PoPMeanTTEF all power plants in this PowerCorp population was 200 (358.300 increments x 0.558 increments per month = 199.764 months) or 16.6 (199.764 increments/12 months=16.647) years. By comparison the PoPMeanTE for the study data was 0.76301 for the 14 year period of the study.

Figure 5-4. Summary of Results of the CAPEM Excursions for PopMeanTE and PopMeanTTEF





Mean = 0.76687

Mean= 358 Increments (16.7 years)

5.7.1 Analysis of Variance

To determine the significance of each flocking factor and the various combinations of flocking factors on the results of the experiment an analysis of the variance among and between them was conducted. The speed with which the CAS ABM simulation is able to complete the necessary 1296 excursions for each experiment and the ability of the statistical packages to handle the volume of resulting data enabled a full 46 factorial experiment. As shown in the table below all four flocking factors at all six levels of adaptability (0, 5, 10, 15, 20, 25) were examined. Note also that the data in this model is balanced (all factors have the same number of cases) and the factors are all fixed (levels of all factors can be and are controlled) so either the Balanced ANOVA or the General Linear Model (GLM) can be used.

The GLM was used primarily out of familiarity and because it allows for analysis of a wider range of possible future analytical situations, balanced and unbalanced. GLM allows for use of covariates and enables multiple comparisons with other statistical methods such as Tukey, Dunnett, Bonferroni, or Sidak (Minitab Inc., 2007). Up to 31 factors can be analyzed at one time. The statistical model for this test is specified as:

Equation 5-1. $y_{ijkl} = \mu + a_i + b_j + c_k + d_l + ab_{ij} + ac_{ik} + bc_{jk} + abc_{ijk} + abd_{ijl} + acd_{ikl} + bcd_{jkl} + abcd_{ijkl} + \epsilon_{(ijkl)}$.

Where μ, is the mean of the population; a_i (alignment vector); b_j (cohesion); c_k (separation turn); d_l (separation distance) and $\epsilon_{(ijkl)}$ is the error term for the sum of squares of the residual. The results of the test are shown in Table 5-2, below.

Table 5-2. Results of ANOVA for PopMeanTE

General Linear Model: PopMeanTE versus Aln, Coh, SepTurn, SepDist

Factor	Type	Levels	Values
Aln	fixed	6	0, 5, 10, 15, 20, 25
Coh	fixed	6	0, 5, 10, 15, 20, 25
SepTurn	fixed	6	0, 5, 10, 15, 20, 25
SepDist	fixed	6	0, 5, 10, 15, 20, 25

Analysis of Variance for PopMeanTE, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Aln	5	0.03291	0.03291	0.00658	9.81	0.000
Coh	5	0.10829	0.10829	0.02166	32.28	0.000
SepTurn	5	2.58295	2.58295	0.51659	769.99	0.000
SepDist	5	4.15985	4.15985	0.83197	1240.08	0.000
Aln*Coh	25	0.12810	0.12810	0.00512	7.64	0.000
Aln*SepTurn	25	0.02482	0.02482	0.00099	1.48	0.063
Aln*SepDist	25	0.08975	0.08975	0.00359	5.35	0.000
Coh*SepTurn	25	0.01879	0.01879	0.00075	1.12	0.313
Coh*SepDist	25	0.23357	0.23357	0.00934	13.93	0.000
SepTurn*SepDist	25	2.34900	2.34900	0.09396	140.05	0.000
Aln*Coh*SepTurn	125	0.10998	0.10998	0.00088	1.31	0.020
Aln*Coh*SepDist	125	0.19744	0.19744	0.00158	2.35	0.000
Aln*SepTurn*SepDist	125	0.09174	0.09174	0.00073	1.09	0.247
Coh*SepTurn*SepDist	125	0.09017	0.09017	0.00072	1.08	0.289
Error	625	0.41931	0.41931	0.00067		
Total	1295	10.63669				

S = 0.0259018   R-Sq = 96.06%   R-Sq(adj) = 91.83%

Table 5-3. Results of ANOVA for PopMeanTTEF

General Linear Model: PopMeanTTEF versus Aln, Coh, SepTurn, SepDist

Factor	Type	Levels	Values
Aln	fixed	6	0, 5, 10, 15, 20, 25
Coh	fixed	6	0, 5, 10, 15, 20, 25
SepTurn	fixed	6	0, 5, 10, 15, 20, 25
SepDist	fixed	6	0, 5, 10, 15, 20, 25

Analysis of Variance for PopMeanTTEF, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Aln	5	208501	208501	41700	24.90	0.000
Coh	5	279034	279034	55807	33.32	0.000
SepTurn	5	16141180	16141180	3228236	1927.59	0.000
SepDist	5	48160455	48160455	9632091	5751.36	0.000
Aln*Coh	25	1176717	1176717	47069	28.10	0.000
Aln*SepTurn	25	75105	75105	3004	1.79	0.011
Aln*SepDist	25	612082	612082	24483	14.62	0.000
Coh*SepTurn	25	47867	47867	1915	1.14	0.287
Coh*SepDist	25	479979	479979	19199	11.46	0.000
SepTurn*SepDist	25	5997773	5997773	239911	143.25	0.000
Aln*Coh*SepTurn	125	331516	331516	2652	1.58	0.000
Aln*Coh*SepDist	125	2232471	2232471	17860	10.66	0.000
Aln*SepTurn*SepDist	125	150840	150840	1207	0.72	0.988
Coh*SepTurn*SepDist	125	155650	155650	1245	0.74	0.979
Error	625	1046719	1046719	1675		
Total	1295	77095889				

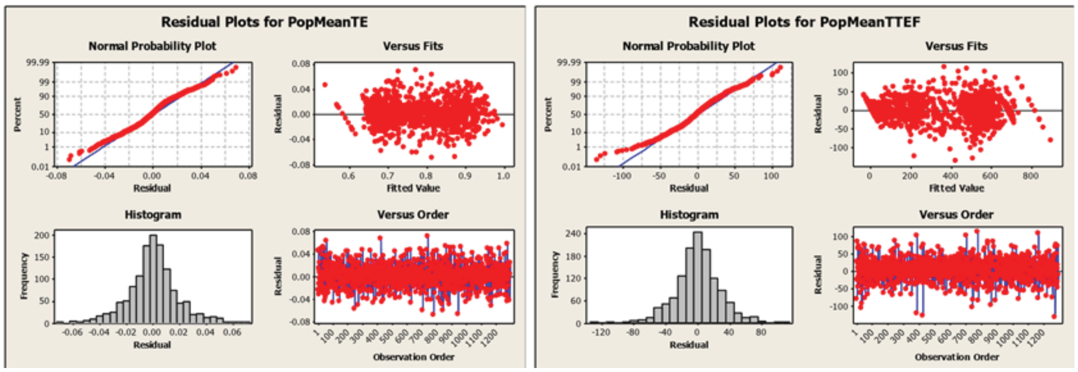
S = 40.9237   R-Sq = 98.64%   R-Sq(adj) = 97.19%

With a sample standard deviation of PopMeanTE of 0.025 out of a possible 9.767 and of PopMeanTTEF of 40.9 out of a possible 253.7 it is observed that the variability of the sample means for both TE and TTEF are relatively small. As noted by the high R^2 and adjusted R^2factors, both greater than 90%, the percentage of response variable variation that is explained by these relationships is high. The pvalues, as shown in Table 5-2 above, for all single factors and for all but one combination of two flocking factors (cohesion, separation turn) are below 0.05 indicating that all these flocking factors and combinations of factors are significant, offering multiple policy options to decision-makers. The same is true for both PopMeanTE and PopMeanTTEF. Two combinations of three factors are indicated as significant (aln*coh*septurn and aln*coh*sepdist) and two are not (aln* septurn*sepdist and coh*septurn*sepdist). By definition for ANOVA the highest order combination (four) is assumed to be insignificant.

For scoping purposes an analysis of only the individual factors and two factor combinations is documented here. Separate ANOVAs were run with only single and two factor variances and resulted in R^2 factors of 87+% and 93+%. When compared to the R^2 factors of 91+% and 97+% shown for the ANOVA including the threefactor variances, it is observed there was relatively little difference in the explanatory value between the two ANOVA models. Given the desire to limit the size and scope of this research and given that three-way interactions are at times overly complicated to explain and use, it decided to include only the single and two-factor interactions in this narrative. Figures 5-2 and 5-3 provide the three-factor results for those who may be interested.

Also of note, when the data and the residuals for the ANOVA were tested there was an assumption of normality. However, both the Anderson-Daring and Kilmogorov-Smirnov tests indicated a level of non-normality. The non-normality is due to a relatively small number of data points on the tails of the distributions to which both tests are particularly sensitive. Given however the large number of samples (1296), an inspection of the histograms and plots shown below and given our knowledge of the data points in question, the ANOVA was considered sufficiently robust for purposes of this research. The plots below are intended to indicate the overall normality or skewness of the data. The normal probability plot indicates whether the residuals of the data are normally distributed, whether other variables are influencing the response, or if outliers exist in the data. Based on this plot, the residuals appear to be randomly scattered about zero. No evidence of nonconstant variance, missing terms, or outliers exists. The residual values versus the fitted values indicate whether the variance is constant, if nonlinear relationship exists, or outliers exist in the data. The residuals versus order of the data plot indicate whether there are systematic effects in the data due to time or data collection order.

Figure 5-5. Results of Normality Test of ANOVA Residuals



Recall that the 1296 excursions are a deliberate sequencing of all levels of adaptability (0, 5, 10, 15, 20, 25) of the four flocking factors consistently sequenced in order (alignment turn, cohesion turn, separation turn and separation distance). This is not a sample of or a subset of the population of possible combinations of levels and factors. It is the entire population. Consequently there is no concern for this set of CAPEM excursions being anything other than representative of the full range of possibilities, normal or otherwise. The sequence of excursions deliberately include samples at the extremes of the possible set such as (0,0,0,0) and (25,25,25,25). In the first extreme combination (0,0,0,0) no factors are active completely contrary to logical or expected coordinated motion among agents. In the second extreme combination (25,25,25,25), all factors are so adaptive as to be almost completely unconstrained or without effect of the rules in their behavior. The sequence of excursions also includes those that would cause flocking behaviors that are contrary to logical or expected coordinated motion among agents such as (0,0,25,25) when no alignment or cohesion are involved, yet there is maximum separation. The agents are simply focused on separating themselves with no guidance toward the efficient frontier. Given that this is an ANOVA of the entire range of possible 1296 excursions, given the overall normal appearance of the data on the histogram and given an understanding of the data increases confidence that the ANOVA is sufficiently robust to provide a reliable indication of the significance of the factors and their interactions.

Also influencing this result is the nature of the study data itself. This was a study of deregulated power plants. While regulation caused a number of inefficiencies these plants were already operating in a reasonably efficient manner from the beginning of time period (1986) as compared, for example, to a population of plants which were new start-ups or whose starting condition were completely random. The lowest starting technical efficiency of the 30 power plants is 0.600. The lowest starting TE of the population of 82 power plants was 0.555. This fact about the nature of the initial TE of the population of power plants results in a higher initial PopMeanTE and a reduced range of possible improvement in PopMeanTE. It also reduces the possible improvements in PopMeanTTEF, the time required to achieve maximum efficiency. Being already at an elevated level of individual TE, power plants have less distance to travel to achieve the maximum efficiency and move quickly to the benchmark resulting in a less dramatic result of this experiment than might otherwise be achieved. Having less time to achieve maximum efficiency the overall change on system behavior is less than it would be for a more initially diverse population. Such a situation might bias the results and be cause for a non-normal test of the ANOVA residuals. The normality of the vast majority of the ANOVA test residuals is encouraging and reinforces the belief that the ANOVA is providing reliable indications of significance for the factors of flocking and their interactions.

5.7.2 Analysis of the Means

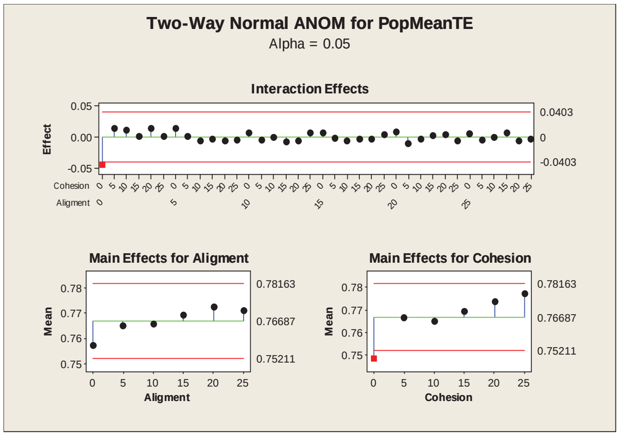
The Analysis of the Means (ANOM) provided below offers a different and complimentary look at the effects of the interactions between flocking factors. From The ANOVA provides a strong indication that all combinations of two of the four flocking factors have a significant effect on increasing PopMeanTE and reducing PopMeanTTEF. The ANOM provides a more detailed look at the pattern of these effects.

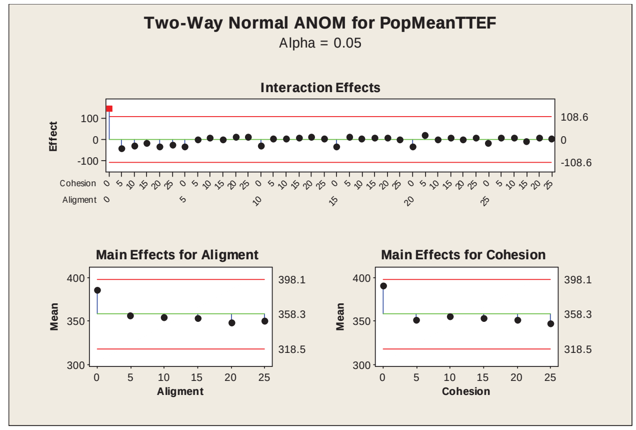
5.7.2.1 Alignment and Cohesion

Shown in Figure 5-6 below, for example, are the pattern of effects on PoPMeanTE and PopMeanTTEF of alignment, cohesion and their interactions at each of the 6 levels (0,5,10,15,20,25). The horizontal red lines in the figure show the limits of the expected effects of the flocking factors between which, the null hypothesis is true (i.e., the means of the population were the same). Between the lines the specific combination of factors and levels do not have a significant effect on PoPMeanTE and PoPMeanTTEF respectively. When the value of the effect falls outside the limits it is highlighted by a red dot showing its significance and showing the direction of the effect, above or below the limits.

From the upper plots in Figure 5-6 below, it can be seen that when both alignment and cohesion are zero (i.e., the effect of the power plants being unable to adopt by means of a combination of alignment and cohesion) there is a significant decrease in PopMeanTE and a significant increase in the PopMeanTTEF. The TE would be lower and it would take longer to achieve the maximum collective efficiency, not welcome news to a PowerCorp decision-maker. At all other combination of levels of these two factors the values of TE are within the expected range but notably all values for TE are greater and all values of TTEF are less than when the level of both factors is zero.

Figure 5-6. Effects of Alignment and Cohesion on PopMeanTE and PopMeanTTEF





From the lower plots in Figure 5-6 it can be seen that when only one factor, alignment is considered all values of TE are within the expected range. When only cohesion is at level zero the effect is significant with an undesirable impact on both TE and TTEF. At all other levels of these two factors the values of TE and TTEF are within expected range. Notably, when considered as a single factor and the level increases there is a positive effect on both TE and TTEF compared to these factors at level zero. Note also however, that the increases are tapering off indicating that levels of adaptability beyond 15 or 20 degrees do not have as much effect and are therefore not as helpful to PowerCorp decision-makers.

TE and TTEF. At all other levels of these two factors the values of TE and TTEF are within expected range. Notably, when considered as a single factor and the level increases there is a positive effect on both TE and TTEF compared to these factors at level zero. Note also however, that the increases are tapering off indicating that levels of adaptability beyond 15 or 20 degrees do not have as much effect and are therefore not as helpful to PowerCorp decision-makers.

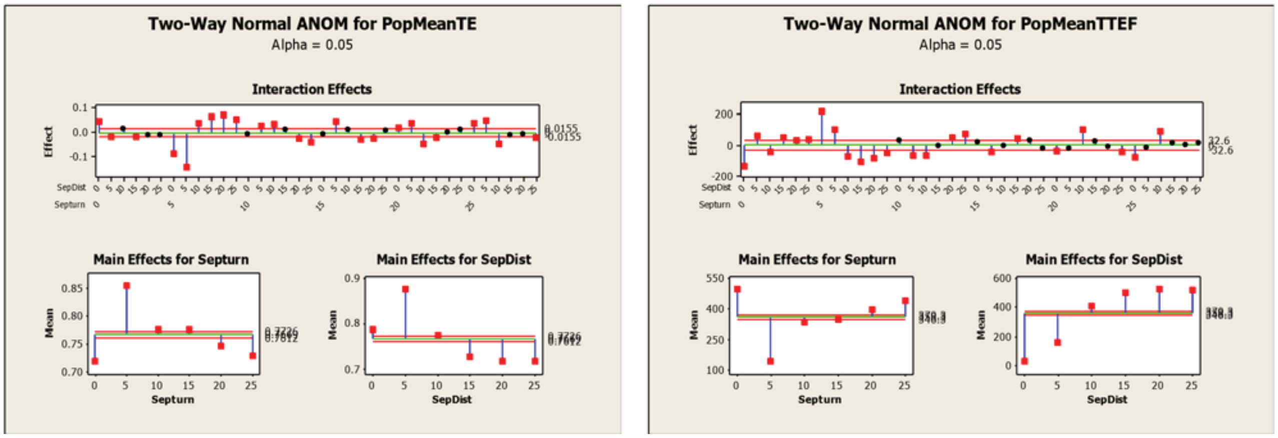
With respect to the hypotheses it can be observed that one of these factors, cohesion, has a significant effect, albeit negative. It can also be observed that as the level of either of these factors increases there is positive effect on both TE and TTEF.

5.7.2.2 Separation Turn and Separation Distance

From the upper plots in Figure 5-7 below, it is observed that when the factors of separation turn and separation distance are both zero (i.e., the effect of the power plants being unable to adopt by means of a combination of these factors) there is a significant increase in TE and a significant decrease in the TTEF. The TE would be higher and it would take less time to achieve the maximum collective efficiency, welcome news to a PowerCorp decision-maker. In contrast to the results for alignment and cohesion numerous combinations of levels of these factors are significant. Also in contrast to the factors of alignment and cohesion the effect of the change (increase) of levels of separation turn and separation distance on TE and TTEF after both are zero, is not always positive. The pattern oscillates in an erratic manner being both positive and negative in a seemingly unpredictable manner.

The implication is that PowerCorps is better off not attempting to keep its plants from achieving the same TE and attempts to increase the levels of the two separation factors has an erratic effect on their ability to continuously improve TE and reduce TTEF.

Figure 5-7. Effects of Separation Turn and Separation Distance



From the lower plots in Figure 5-7 it is observed that when separation turn alone is considered, the increase in level to 5 degrees has a dramatic, positive effect on both TE and TTEF. As the level increases these positive effects quickly diminish and at 20 degrees become negative for both TE and TTEF. When separation distance alone is considered the increase in level to 5 degree likewise has a dramatically positive effect on both TE and TTEF. As the level increases these positive effects also quickly diminish, and go negative for both TE and TTEF, this time at the 15 degree level.

Translated into power plant decision-making this indicates that an ability to respond with less warning to a potential problem is more important that how great the change when the warning comes. For PowerCorp this indicates that smaller changes in the use of fuel or labor will be sufficient to avoid problems when they become evident. Fostering a culture of flexibility over investment in long term forecasting of issues may be an appropriate interpretation. Also noteworthy is the pattern of effects as the level of each factor increases. At between 10 and 15 degrees the effects of increasing levels of adaptability shift from helpful (reducing

PopMeanTTEF) to hurtful (increasing PopMeanTTEF). For PowerCorp this indicates a need to avoid over reaction to short term changes in TE.

5.8 Findings: Patterns of Emergence and Policy Implications of this Analysis

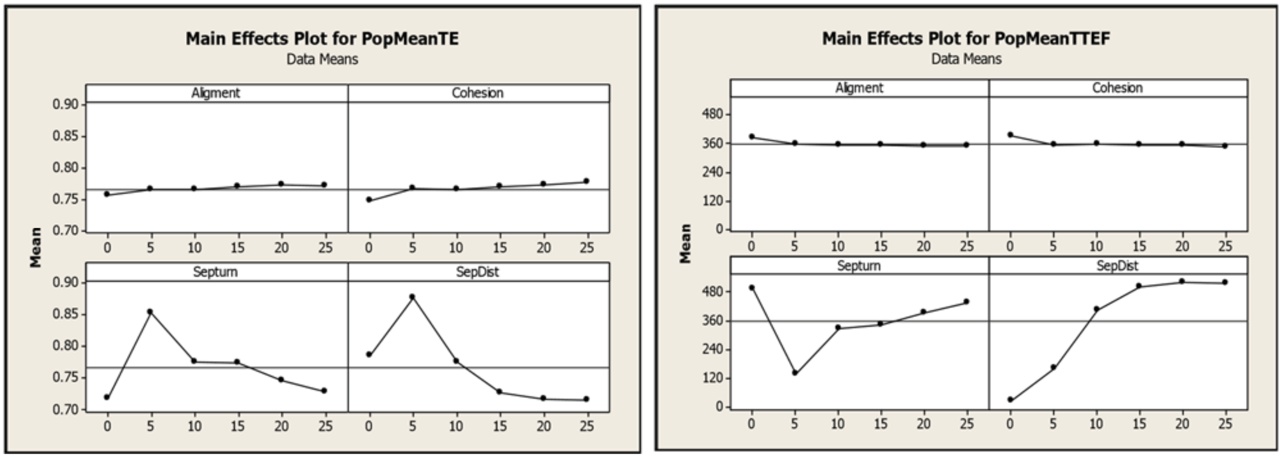
Foremost in this experiment is the desire to understand if one or more of the flocking factors has an impact on the collective behavior of the population of ADMUs, and if so, what that impact might be. Consider then how this information might be used by decision-makers of a management system to achieve their desired goals. Graphical analyses shown below can help us further visualize and understand the results of this experimentation.

5.8.1 The Effects on Policy of Single Factors - Alignment (Hedging) or Cohesion (Best Practice)

As shown in the upper plots in Figure 5-8, below, when the ability of the population of power plants to align increases from 0 to 5 degrees the TE increases and the TTEF decreases. For the PowerCorp decision-maker this translates to hedging (following the average policy decisions of other inefficient power plants) as a viable policy option. Increasing levels from 5 to 10 degrees there is further improvement in both TE and TTEF. After 10 degrees there seems to be little additional value to having additional ability to align (hedge) to achieve policy goals.

A very similar pattern is observed for cohesion, that is, the employment of best practices as options for achieving improved production efficiency offers viable yet limited options for achieving PowerCorp goals. Knowing the limitations on these options can be as helpful to decision-makers as knowing the options themselves.

Figure 5-8. Main Effects of the Flocking Factors on PopMeanTE and PopMeanTTEF



Through this analysis the PowerCorp decision-makers may find that it better to align and or cohere than not to do so and that it doesn't take a high degree of either factor to have a positive impact on achieving their goals of increased PopMeanTE and reduced PopMeanTTEF. These findings imply that investing in power plants to increase their ability to adopt further or more quickly in their ability to align or cohere will not result in a significant return on investment. This finding is quite unexpected. While as expected it is found that alignment and cohesion options exist, but we find that they are far more limited in range and effect than expected.

5.8.2 The Effects on the Use of Fuel and Labor in a Separation Turn Only Policy (Changing Policy Direction)

As show in Figure 5-8, above, when the ability of the population of power plants to separate (maintain a robust diversity of approaches) is zero TE decreases and TTEF increases. Changing the level of adaptability to separation turn in this case would equate to changing the use of fuel relative labor to avoid having exactly the TE any other another ADMU in the population (i.e., its nearest neighbor in the production possibility space). A change of level in degrees from 0 to 5 equates to a change in the proportion of fuel to labor by 5 degrees change / 90 degrees of change possible = 0.055 % change in its current state. To achieve a change in policy of 5 degrees adaptability to separation turn when , for example, the proportion of labor to fuel is currently 100 laborers for every 1000 BTU of fuel, would require the addition of roughly 6 laborers for the same amount of fuel.

At this point in this research the interpretation of separation turn as maintaining diversity of policies is hypothetical deriving deductively from the stated definitions of TE. This notion is further supported by an increasing number of studies on emergence related to the need for this kind of diversity in policy making (Sawyer, 2005) but it is as yet still hypothetical. Further clarification and analysis of this portion of the metaphor will require collection of data that does not currently exit and must be left to future research.

As the level of separation turn changes from 0 to 5 degrees there is dramatic increase in TE and a dramatic decrease in the time required by the population to achieve maximum efficiency. At levels 5-15 TE increases and TTEF decreases but not as dramatically. At levels 20-25 the effect of separation turn on TE and TTEF actually reverses having an undesirable effect of the PowerCorp goals. This indicates to a PowerCorp decision-maker that separation turn offers multiple impactful options. PowerCorp would benefit significantly from maintaining a small degree of policy diversity among power plants but that any effort to achieve greater adaptability would be unnecessary, even counterproductive.

5.8.3 The Effects on the Use of Fuel and labor of a Separation Distance only Policy (timing or knowing when to make the policy change)

When the population of power plants pursues a policy of maintaining a certain separation distance (i.e., lead time for making a decision / policy change) is zero the power plant is in fact choosing not to forecast policy changes but to make them ad hoc when a consequence occurs. To maintain an appropriate separation distance a

PowerCorp power plant must seek apriori to maintain a TE (i.e., the proportional use of fuel to labor). To do so it must be able to sense, detect or have information on other power plants prior to a “collision” or both having the same TE. As explaioned in Chapter 3 this is achieved in CAPEM by monitoring and measuring the corresponding number of units of distance (patches) on in CAPEM PPS. It must also be defined by the change in direction from the power plant to its nearest neighbor (again in terms of TE) This is measured along the two axes in CAPEM PPS. Distance and direction compute to a specific location on the PPS and to a specific TE for the power plant. From this specific TE a specific amount of fuel and labor to be used by both the power plant being monitored and the approaching power plant can be calculated. Achieving a separation distance of 5 units translates in this illustrative example to a difference of 500 BTUs or 6 employees or a combination of the two that graphically equates to the length of the hypotenuse drawn between the intersections of their values on their respective axes.

As with separation turn, at this point in this research the interpretation of separation distance as maintaining diversity of policies is hypothetical, deriving deductively from these definitions of TE. This notion is further supported by an increasing number of studies on emergence related to the need for this kind of diversity in policy making (Sawyer, 2005) but it is as yet still hypothetical. Further clarification and analysis of this portion of the metaphor will require collection of data that does not currently exit and must be left to future research.

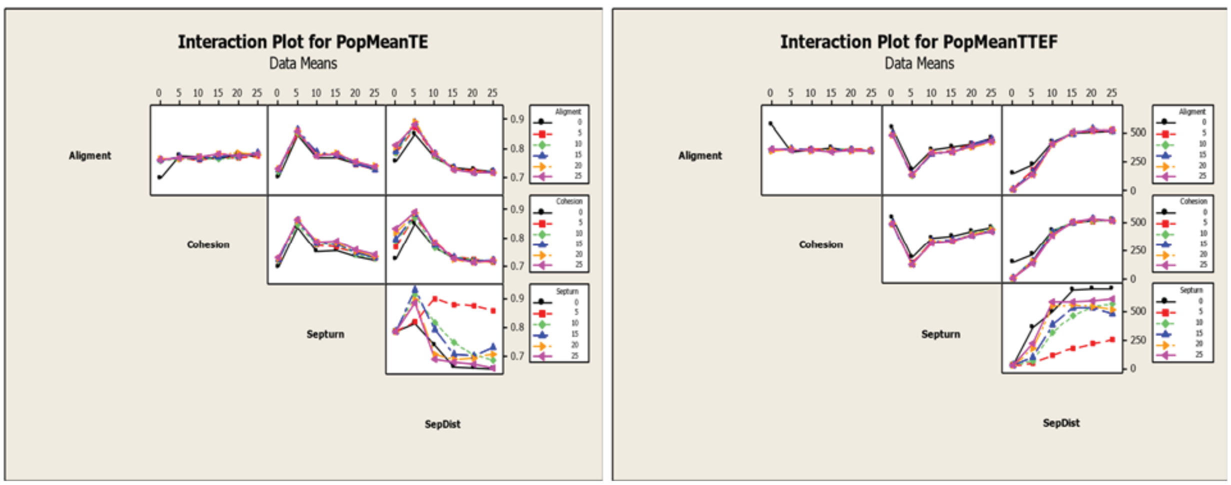
As shown in Figure 5-8 above, when the separation distance is at level 0 or 5 the TE is increased and TTEF is markedly decreased, both being desirable results and offering a viable policy option. At level 10, TE is increased, a desirable result. At the same time TTEF is also markedly increased, an undesirable result if, as was assumed, TE and TTEF are equally important. This is a mixed result not seen elsewhere in the results of this research and not a viable policy option. At level 15 and beyond, TE is decreased and TTEF is increased both being undesirable results. The overall finding for separation distance then is that maintaining a distance of 5 units is not only viable option but a very effective one given the magnitude and significance of the effects as shown by the ANOM. Translated to practical terms this indicates that if individual power plants maintain a small degree of diversity in its policies (for use of fuel and labor) the collective TE and TTEF is improved. PowerCorp would seek to influence its members to do so.

5.8.4 The Effects of Pairwise Combinations of the Flocking Factors

Figure 5-9, below, provides us with an understanding of how the interactions between any two of the four flocking factors affect the behavior of the PowerCorp population of power plants. The value of this plot over previous plots is the ability to compare each combination of factors at all levels (0, 5, 10, 15, 20, 25) simultaneously. Each cell in the plot displays each factor at all six levels of adaptability overlaid on one another to show the variability or lack of variability among the levels. For the PowerCorp decision-maker this offers insights into which factors and which levels of these factors offer the greatest policy insights and the greatest opportunity for influencing change.

Immediately apparent is the tight grouping of all plots for all combinations of factors except those that include separation distance. Most notably among the factors that include separation distance is the variability for the combination of separation turn and separation distance. Most notably in this cell is the marked difference between levels 0, 5 and the other levels. The PowerCorp decision-maker would need to be very careful to avoid policies that make decisions concerning separation turn at any distance other than 5 units. The significance of this factor as seen in this analysis of single factor results is of such magnitude and effect that it dominates the others. It is observed that this is so even when considered in combination. The means of achieving these policy changes was explained in the previous sections of this paper, corresponding to the kind of change desired (i.e., change in use of fuel and labor to achieve TE that are in a different direction from the current state and are different in distance along a specified axis (in units of the PPS). As indicated by the lower most and right most cell in this figure, the relationship between separation turn and separation distance is the most sensitive and most impactful and will therefore require closest monitoring by decision-makers when making policies on the use of fuel and labor.

Figure 5-9. Effects of the Interaction Between All Combinations of Two Flocking Factors



Numerous others insights can be gained from these plots depending on the needs of the decision-maker. As ability of the population of power plants to cohere, for example, increases from zero to five degrees and the ability of the population of power plants to align remains at 5 degrees, there is little effect on the time required for the population to achieve optimal efficiency or the PopMeanTE. For a PowerCorp decision-maker, this is limiting to his options but is still valuable information, indicating that a mixed policy of 5 degrees for each factor is the worth pursuing and that any other combination of the two factors provides little advantage.

As a second example, pursuing a policy that combines, for example, changes in levels of cohesion and separation for all levels of separation when cohesion is at level 25. The insight for the decision-maker is that the influence of maintaining diversity of polices can be achieved at ever increasing rates as the ability of power plants to adapt to cohere to the policies of the most efficient power plants increases from 0 to 25 degrees. The same is true for a mixed policy of alignment (or cohesion) and separation turn (changing policy direction to achieve separation). There is a distinct advantage to a combined policy at 5 degrees for each factor. At other degrees of adaptability for either alignment or cohesion there is less advantage. In aggregate we observe that following a mix of policies is nearly always an advantage over a policy of zero adaptability to alignment or cohesion. Said another way, while the factors alignment and cohesion had far less effect than expected, a mixed policy including alignment and or cohesion is better than policies with no alignment to cohesion at all. Notably, it is indicated by the minimal effects on TE and TTEF that the plots is followed to the right (to greater levels of adaptability), the number of viable policy options become very limited. The ability either to pursue a change in policy direction (separation turn) or maintain current policies (separation turn at zero degrees) even in combination with any other flocking factor is in many cases counterproductive. Decision-makers must take care to closely scrutinize the specific situation. With regard to the hypothesis numerous viable options were found when the flocking factors are considered individually and in combinations. The number of these options are however smaller and the effects more limited than expected.

5.8.5 Conclusions With Respect to the Hypotheses

Having conducted the foregoing tests and achieved the foregoing findings the following conclusions can be made with regard to the experimental hypotheses:

5.8.5.1 Hypothesis #1: The Influence of Adaptability to Individual Flocking Factors on the PopMeanTE

Hypothesis #1 is supported. This hypothesis asserts that as the levels of adaptability (i.e.,0,5,10,15,20,25) of each of the flocking factors (alignment turn, cohesion turn, separation turn, separation distance) increase, the population mean technical efficiency (PopMeanTE) increases. That is, as the members of PowerCorp increase their ability to adapt more quickly to the influence of each of the four flocking factors, the collective population mean technical efficiency of PowerCorp (PopMeanTE) will increase. From the p-values in the ANOVA it is indicated that all four factors were below 0.05, the 95% confidence level, telling us that all four flocking factors have a significant influence on the population mean technical efficiency (PopMeanTE). The ANOM confirms the ANOVA finding, that all four factors are in fact significant in one way or another and shows us that all combinations of factors have at least one level of adaptability that causes a significant change in PopMeanTE.

From the ANOM and the analysis of the main effects plots in the previous section, we also learn that without the flocking factors of alignment and cohesion (each factor at level 0) PoPMeanTE decreases. When these factors are active (at level 5+) the effect improves. At levels 5 and 10 the effect results in an increase in the PopMeanTE. This is a desirable result for the PowerCorp decision-maker and supports the hypothesis. This conclusion however, comes with limitations, as described above. This result tells us that only if the individual power plants in PowerCorp are adaptable to alignment and cohesion at levels 5 and 10 will these factors provide PowerCorp with viable options to significantly increase PopMeanTE. If they are not sufficiently adaptable, adherence to the factors of alignment and cohesion can be counterproductive. Nevertheless, there are multiple levels of adaptability at which alignment and cohesion increase PopMeanTE, therefore the hypothesis is supported.

Likewise, the ANOM confirms the ANOVA findings for separation turn and separation distance as well. Given the range of levels of separation turn and separation distance that are significant, these two factors, offer the decision-maker the most numerous positive effect options for policy-making, more so than with cohesion and separation. As with alignment and cohesion there are limitation on the use of these factors. Only at levels of adaptability of 5 and 10 will the use of these factors individually result in an increase of PopMeanTE and or a decrease of PopMeanTTEF. With these findings hypothesis #1 is supported.

5.8.5.2 Hypothesis #2: The Influence of a Combination of the Flocking Factors on the PopMeanTE

Hypothesis #2 is supported. This hypothesis asserts that as the levels of adaptability (0, 5,10,15,20,25) of selected combinations of the flocking factors (alignment turn, cohesion turn, separation turn, separation distance) increase, the population mean technical efficiency (PopMeanTE) increases. That is, as the members of PowerCorp increase their ability to adapt to the use of certain identified combinations of the four flocking factors, the collective population mean TE of PowerCorp power plants will increase. From the ANOVA it is determined that the p-value for all but one combination of two flocking factors was below 0.05 the 95% confidence level. From the ANOVA it is found therefore that all but the combination of cohesion turn and separation turn have a significant influence on the overall population mean TE. The ANOM confirms the ANOVA finding, that all but one combination of two factors are in fact significant and that all remaining combinations have at least one level of adaptability that causes a significant change in the PopMeanTE.

It is observed in the interaction plots in Figure 5-9 above, that when alignment and cohesion are both at level zero, the effect is to significantly decrease PopMeanTE. All other combinations of the two factors however, result in an increase in the TE when compared to not using these two factors in combination. The increase in PopMeanTE is small but positive. This would limit the options and magnitude of effect of the options available to PowerCorp decision-makers but based on the ANOM and the Interaction plots it is clear that use of these two factors is an improvement over not using them at all (both at level 0). Five other combinations of two factors offer significant improvements in the PopMeamTE, notably those combinations of separation turn and separation distance the greatest effect occurring when these two factors change from both being zero to both being employed at adaptability level 5. To the PowerCorp decision-maker this is saying that a combination of alignment (hedging) and separation turn (maintaining diversity of policies) requires a relatively small level of adaptability to be able to employ this option to influence PopMeanTE. The same effect occurs with the interaction of pairs of policy options using separation distance (the level of risk taken before making a decision to diversify is made) and each of the three other flocking factors. The combinations of these pairs of factors suggest to the PowerCorp decision-maker that if he waits until the distance is at level five (relatively high risk) they can have the greatest effect on the PoPMeanTE. At zero and at greater distance than level 5 (less risk) the effect could in fact be detrimental. So, while only a small number of levels and combinations of factors increase the PopMeanTE, there are at least five that do. This hypothesis is supported.

5.8.5.3 Hypothesis #3: The Influence of the Individual Flocking Factors on the PopMeanTTEF

Hypothesis #3 is supported. The reasoning for the support of this hypothesis is that a positive or desirable effect is the decrease of TTEF. This hypothesis asserts that as the levels of adaptability (0,5,10,15,20,25), of each of the flocking factors (alignment turn, cohesion turn, separation turn, separation distance) increase, the population mean time to achieve the efficient frontier (PopMeanTTEF) decrease. That is, as each population of power plants increases its ability to adapt (0, 5,10,15,20,25), responding more quickly to the influence of each of the four flocking factors individually, the time required for PowerCorp to achieve its goal of maximum efficiency will decrease. From the ANOVA it is determined that the pvalues for all four factors were well below 0.05, the 95% confidence level, indicating that all four flocking factors have a significant influence on the time to achieve maximum technical efficiency (PopMeanTTEF). The ANOM confirms that all four factors are in fact significant and that all factors have at least one level that causes a significant change in PopMeanTTEF.

From the ANOM it is observed that without the flocking factors of alignment and cohesion (each factor at level 0) PoPMeanTTEF increases. When these factors are active (level 5 and beyond) the PopMeanTTEF decreases and continues to decrease as the level increases, a desirable result for Power Plant decision-makers is achieved and is one that supports the hypothesis. From the ANOM in Figure 5-9 it is observed that the flocking factors of separation turn and separation distance also have significant affect at all levels of adaptability. Without separation turn (level 0) the affect is to significantly increase PopMeanTTEF, an undesirable effect. When separation turn is in effect (at levels 5,10,15) the affect is to significantly decrease PopMeanTTEF, a desirable effect and one that supports the hypothesis. Surprisingly, when separation turn is at levels 20, 25) the effect is to again increase PopMeanTTEF, an undesirable effect. There is an oclation of the effects due to the effects of the interactions between the two factors. Likewise for separation distance, without the factor of separation distance (level 0), the effect is to markedly decrease PopMeanTTEF, a desirable effect, but not one that supports the hypothesis. When separation distance is active (at level 5) the effect is to also significantly decrease PopMeanTTEF, a desirable effect and one that supports the hypothesis. Beyond level 5 the effect of separation distance is to significantly increase PopMeanTTEF, returning again to an undesirable result and one contrary to the hypothesis.

For the decision-maker there are therefore numerous levels of adaptability for each of the four flocking factors that offer options for deceasing PopMeanTTEF. As with options for influencing PopMeanTE there are limitations on the use of the levels of adaptability and flocking factors but numerous options are available. This hypothesis is supported.

5.8.5.4 Hypothesis #4: The Influence of a Combination of the Flocking Factors on the PopMeanTTEF

Hypothesis #4 is supported. The reasoning for support of this hypothesis is the same as for hypotheses #2 except that a positive or desirable effect acts to decrease TTEF rather than increase as was desirable for TE. This hypothesis #4 asserts that as the levels of adaptability (0,5,10,15,20,25), for a combination of the flocking factors (alignment turn, cohesion turn, separation turn, separation distance) increase the population mean time to achieve the efficient frontier (PopMeanTTEF) will decrease. That is, as the members of PowerCorp increase their ability to adapt and use some combinations of the four flocking factors, the overall mean time to the EF of the population of PowerCorp power plants (PopMeanTTEF) will decrease.

Once again, from the ANOVA it is determined that the p-value for all but one combination of two flocking factors was below 0.05, the 95% confidence level. This was the one of the combination of cohesion and separation turn indicating to a power plant decision-maker that combining a policy of coherence (adhering to best practice) combined with a policy separation (maintaining diversity of policies or avoiding competition between two very similar power plants) does not significantly influence/decrease the time it will take to achieve maximum TE. From the ANOVA it is found that all other combinations of flocking factors have a significant influence on the overall population mean TTEF (PopMeanTTEF). The ANOM confirms the ANOVA finding, that all but one combination of two factors are in fact significant and that all but one combination has at least one level of adaptability that causes a significant change in the PopMeanTTEF.

It is observed in Figure 5-9 above, that when alignment and cohesion are both at level zero, the effect is to significantly increase the PopMeanTTEF. All other combinations of the two factors however, result in a significant decrease in TTEF when compared to not using these two factors in combination. No other combination of the two factors results in a decrease that is significant enough to be used to generate options for decision-makers but based on the ANOM it is clear that use of these two factors is an improvement over not using them at all. It is observed in Figure 5-9 above, that when separation turn and separation distance are considered in combination both at level 0 there is a significant decrease in the PopMeanTTEF, a desirable result, but not one that supports the hypothesis. However as separation turn remains zero and separation distance increases in level the results begin to oscillate between increasing then decreasing, then increasing again the PopMeanTTEF. These oscillations continue as both factors increase in levels but the oscillation dampens with increased levels of the variables. Notable among these oscillations are a number of combinations of these two flocking factors that decrease PopMeanTTEF, a desirable result and one that supports the hypothesis. It is found that there are numerous levels of adaptability to multiple combinations of the flocking factors. For the decision-maker there are therefore numerous levels of adaptability for numerous combinations of the four flocking factors that offer options for deceasing PopMeanTTEF. As with options for influencing PopMeanTE there are limitations on the use of the levels of adaptability and the combination of flocking factors but numerous options are available. This hypothesis is supported.

5.8.5.5 Observations on the Comparisons between the Results on PopMeanTTEF and PopMeanTE

It is readily observed that the results for these two estimators are nearly the identical opposite of one another. There is some slight differences observable in the analysis. In Figure 5-8, Main Effects of the Flocking Factors on PopMeanTE and PopMeanTTEF for example, the plots for separation distance appear to be different at levels 0 and 10. If at some point in future research however, it can be shown that PopMeanTE and PopMeanTTEF have, in fact, identically opposite effects, this would offer a pattern of collective behavior that would be of value to decisionmakers. Knowing, for example, the relationship between the level of TE and the time remaining to achieve maximum collective efficiency allows decision-makers to use one as a proxy for the other to gain insights into future system behavior. If data were available for one estimator and not the other the need for additional data gathering would be reduced. Further investigation into this effect is warranted.

5.8.6 Observations on the Effects of Separation Turn and Separation Distance

The flocking factor of separation, unlike the other factors, has two components, separation turn and separation distance. In its internal rules of coordinated motion, an ADMU will prioritize the influence of the rule of separation turn over alignment and cohesion when it reaches a specified distance from its nearest neighbor. Prior to reaching this distance the rules of alignment and cohesion predominate. To gain some initial insights into the impact of these two distinct parameters we conducted some additional analysis.

As indicated by the R^2 values in the ANOVA, that when considering the combination of cohesion, separation turn explains about 20% of the overall variation for both TTEF and TE. In contrast, separation distance in combination with cohesion explains 40% of the variation for TTEF and 60% of the variation for TE. For TTEF the effects of cohesion are not significant while the influence of cohesion on TE is significant. For PowerCorp this implies that if their priority is the final TE without regard to achieving the fastest possible time then pursuing changes of policy for cohesion (by adhering to best practices) is preferable.

Conversely, for TTEF the effects of the interaction between cohesion and separation distance is not significant while this interaction is significant in explaining the variation in TE. The implication for PowerCorp is that a policy of diversity for example may be pursued when also pursuing a policy of cohering to corporation best practices. As described in Dougherty, Ambler and Triantis (2014a, Section 5.5.2) these best practices are the variations in the proportionality of use of fuel and labor as practiced by the most efficient power plants in PowerCorp. Also indicated for the overall use of the flocking metaphor is the need to be selective and careful in the use of the various combinations of factors to be sure to leverage the strengths of the metaphor and avoid its weaknesses. Decision-makers finding an advantage in employing the separation turn at one level, for example, may assume that increasing further the level of adaptability for separation turn would also be their advantage. Knowing, for example, that as was described earlier in this chapter, maintaining adaptability of a power plant for separation distance at level 5 results in significant increases in TE, a decision-maker may be inclined to assume that investment in additional levels of adaptability would follow. Knowing also that adaptability to this factor beyond level 5 results in no further increases in TE permits would help the decision-make avoid making useless investments and faulting the metaphor.

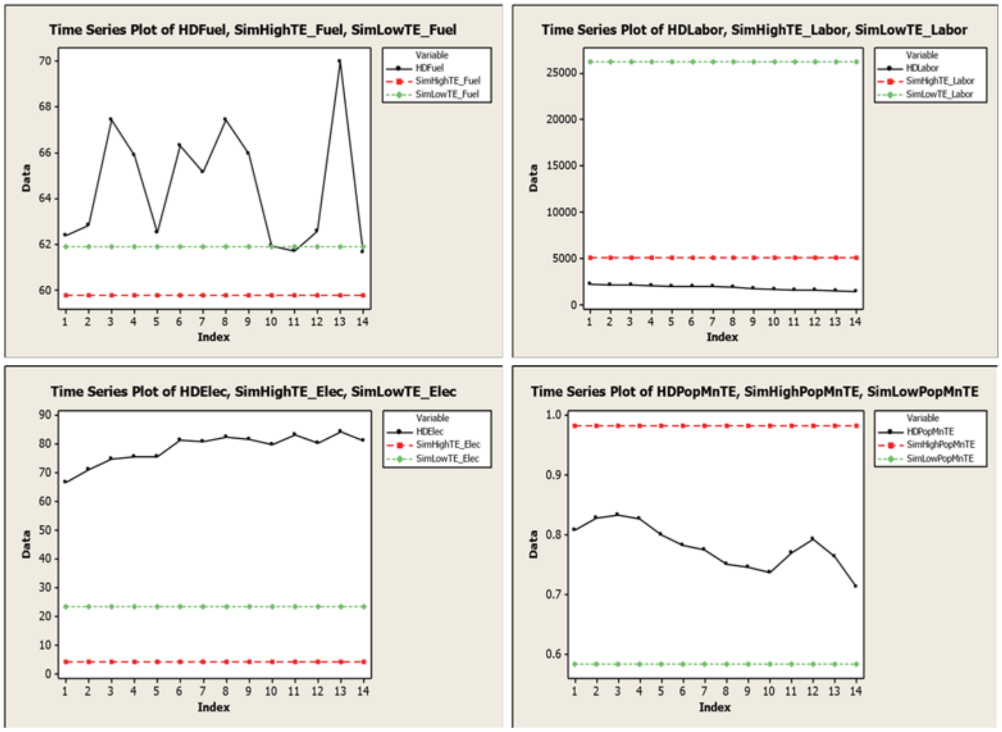
5.9 Initial Comparison of Results – Standard DEA and CAPEM

The CAPEM analysis employed the Rungsuriyawiboon and Stefanou (2003) study data with the express intent of offering a means of anchoring this research in the real world. The comparison is of course challenging given that they are derived from two fundamentally different approaches. Recall, current forms of productive efficiency analysis is physics based, driven by the factors of production and in CAPEM on the other hand decision-making is driven by the four factors of the flocking metaphor. There is little expectation of observing the same patterns of change over the 14 year period much less matching curves for purposes of validation. Nonetheless an initial comparison was made to gain a sense of the comparisons and contrasts.

To develop the standard DEA results a common DEA tool was employed, the DEA Solver, which performed the linear programing calculations on the data for each year of the Rungsuriyawiboon and Stefanou (2003) study. As in CAPEM we considered the envelopment model (input reducing case) and assumed constant returns to scale (the CCR model). The results of the comparison are provided in Figure 5-10 below. Comparisons are made between the results of the annual DEA analysis and the PopMeanFuel, PopMeanLabor, PopMeanElec and PopMeanTE taken at annual points in selected the CAPEM excursions.

In Figure 5-10 the dotted black piecewise linear curve is a time series plot of the DEA snap shots in time of each of the 14 years of data. The connected red square line and the connected green diamonds line display the results of the 1296 CAPEM excursions whose starting location was that of the 1986 date from Rungsuriyawiboon and Stefanou (2003) data. The diamond green line displays the results for the CAPEM excursion that resulted in the highest PopMeanTE, which after all is the main purpose of the analysis. In order to indicate the range of CAPEM results results of the CAPEM excursion that resulted in the lowest PopMeanTE were also displayed. These results are represented by the squared red line. The space between the highest and lowest constitutes the range of overall corporate efficiency that PowerCorp could expect when using the flocking metaphor to guide their decision-making. For the PowerCorp power plant decision-maker this offers insight into the range of possibilities and the possible range of the effects these possibilities will have in reaching their goal of continuously improving productive efficiency (PopMeanTE) and reducing the time needed to achieve their goal (PopMeanTTEF).

Figure 5-10. Comparisons Between Results of Standard DEA Analysis and CAPEM Excursions for PopMeanFuel, PopMeanLabor, PopMeanElec and PopMeanTE



Legend:

- HDFuel, HDLabor, HDElec – the use of fuel and labor and the electricity produced in the historical data
  □ HDPopMeanTE and HDPopMeanTTEF – the population mean TE and TTEF for the historical data
- SimHighFuel, SimHighLabor, SimHighElec – the use of fuel and labor and the electricity produced in the CAPEM excursion with the highest PopMeanTE
- SimHighPopMnTE and HDPopMnTTEF – the population mean TE and TTEF for the CAPEM excursion with the highest PopMeanTE
- SimLowFuel, SimLowLabor, SimLowElec – the use of fuel and labor and the electricity produced in the CAPEM excursion with the lowest PopMeanTE.
- SimLowPopMnTE and SimLowPopMnTTEF – the population mean TE and TTEF for the CAPEM excursion with the lowest PopMeanTE

It can be observed in the upper left most plot that the CAPEM approach and the flocking metaphor-based PowerCorp were very effective in reducing the use of fuel (indicated by having both the SimHighTE line (red) and the SimLowTE (green) lines plotting below the HDFuel (black) line). In only 3 of the 14 years did the standard DEA method use as little fuel as the least technically efficient simulation excursion and then by a very small margin. As was observed in the upper right most plot, the opposite is true of labor. The standard DEA approach’s use of labor and the use of labor in the most technically efficient case of the flocking metaphor approach were similar but in all cases the standard DEA result used less labor.

In the lower left most plot it is observed that the standard DEA approach resulted in the production of markedly greater levels of electricity than were produced by even the most technically efficient case of the flocking metaphor. This is an interesting and valuable observation. It should be remembered however that this research hypotheses, these goals and these measures of effectiveness for the flocking metaphor were focused on increasing technical efficiency and reducing time to achieve maximum efficiency. To avoid confounding the analysis creating within the ADMUs an internal rule seeking to maximize the production of electricity was intentionally avoided.

Within the context of this research the results shown in the lower right most plot provide a more important observation. It is observed that the TE for each of the 14 years of the standard DEA analysis are centered between the least technically and the most technically efficient flocking metaphor driven cases. Strictly speaking it can be observed that the flocking metaphor based decision-making offers policy options that are markedly more technically efficient. Within the strict context of this research it is observed that the value of using the flocking metaphor is supported. Adding maximization of electrical production as an ADMU internal goal would be the next logical step. Doing so in this research would have violated the premises of conducting a bottom-up metaphor driven experiment. Considering the implications of a combined bottom-up, metaphor based and a top-down, physics based approach most is left to future research.

5.10 Conclusions – Case Study

CAPEM extends the analysis of productive efficiency from a top-down, control theory based paradigm driven by the physics of the factors of production to a bottomup, complexity science based paradigm of interacting autonomous entities driven by factors of change (alignment, cohesion and separation) derived from ecosystem metaphor. The physics of the chemical or mechanical processes remain relevant and are employed to supplement the CAS ABM analysis but fundamental drivers of system behavior have changed. The building block concepts of productive efficiency embodied in standard and dynamic DEA (DMU, PPS, EF, PF, the axioms of production, continuous, non-linear change over time) are maintained and associated with the building block concepts of CAS ABM. The theory of both these paradigm have been informed by the knowledge that they can be successfully and usefully combined to form a whole new approach to productive efficiency analysis. The new concepts of efficiency that emerge from this research are approaches from the use of biologically inspired metaphor. It is a new concept of efficiency based on induction versus deduction.

The idea that efficiency can be driven or achieved through the use of flocking factors derived from natural ecosystems rather than a pre-defined production function is new to at least the DEA form of productive efficiency analysis. Treating DMUs as CAS ABM agents is new and offers a whole new way of representing, simulating and understanding the dynamics of productive efficiency. Likewise treating the production possibility set as a CAS ABM environment and embedding the efficient frontier there offers a heretofore unrealized level of definition to the interaction between them. The notion of adaptability of a DMU to their environment and to factors other than or in addition to the factors of production offer new ways to represent, experiment with and think about productive efficiency.

Tables 5-4 and 5-5 below provide a brief summary of the findings and conclusion described in Section 5.8 and 5.9 above.

Table 5-4. Summary - Findings with Respect to the Hypotheses

Findings with Respect to the Hypotheses	
PopMeanTE-single factor variations	Both the ANOVA and ANOM confirms that all four factors are in fact significant (improve TE) for at least one level of adaptability. Alignment and Cohesion improve at level 5 but little beyond this level. Separation Turn and Max Separation Turn offer policy options for improvements of TE at levels 5 and 10 but little beyond those levels. The Hypothesis 1 is supported.
PopMeanTE two factor combination variations	From the ANOVA it is determined all but one combination of two flocking factors (the combination of cohesion turn and separation turn) is significant. The ANOM confirms the ANOVA finding and that all remaining combinations have at least one level of adaptability that causes a significant improvements in the PopMeanTE. Five other combinations of two factors offer the most improvements in the PopMeamTE, notably those combinations of separation turn and separation distance, the greatest effect occurring when these two factors change from both being zero to both being employed at adaptability level 5. Hypothesis 2 is supported.
PopMeanTTEF single factor variations	Without the use of the flocking factors of alignment and cohesion (each factor at level 0) PoPMeanTTEF increases significantly (undesireable). When these factors are active (level 5 and beyond) the PopMeanTTEF decreases and continues to decrease as the level increases (a desirable result for PowerCorp). The Hypothesis 3 is supported.
PopMeanTTEF two factor combination variations	When alignment and cohesion are both at level 0, PopMeanTTEF significantly increases (undesireable). All other combinations of the two factors result in a significant decrease in TTEF when compared to not using these two factors in combination. When separation turn and separation distance are considered in combination both at level 0 there is a significant decrease (desireable) in the PopMeanTTEF. As separation turn remains zero and separation distance increases in level the results begin to oscillate between increasing then decreasing, then increasing again the PopMeanTTEF. These oscillations continue as both factors increase in levels but the oscillation dampens with increased levels of the variables. Hypothesis 4 is supported.

Table 5-5. Summary - Comparisons with Historical Data

Comparisons with Historical Data	
Use of Fuel	Flocking metaphor driven decision-making was very effective in reducing the use of fuel. In only 3 of the 14 years did the standard DEA method use as little fuel as the least technically efficient flocking solution excursion
Use of Labor	The standard DEA driven decision-making employed less labor than even most technically efficient flocking metaphor driven excursion in all 14 years of the comparison.
Production of Electricity	The standard DEA approach resulted in the production of markedly greater levels of electricity than were produced by even the most technically efficient flocking metaphor driven excursion. (Recall that agent goals flocking metaphor were focused on minimizing inputs, increasing technical efficiency and reducing time to achieve maximum efficiency not on maximizing output.)
Technical Efficiency	Flocking metaphor driven decision-making offers selected policy options that are markedly more technically efficient. The TE for each of the 14 years of the standard DEA analysis are centered between the least technically and the most technically efficient flocking metaphor driven cases. Caution is warranted since numerous flocking driven policy options are markedly less efficient.

5.10.1 Use of Ecosystem Metaphors

In CAPEM the individual and collective management system behaviors are explained and understood not by the normal control-theory approach of representing the properties and interactions among the factors of production (fuel and labor), using archetypical patterns of accumulation, or rates of change and their interrelationships. Rather this approach uses a relatively new complex adaptive systems framework using the ecosystem metaphor of flocking (alignment, cohesion, separation), a direct result from the study of the patterns of ecosystems-like behaviors found in nature such as birds, fish and bats. Flocking as an emergent ecosystem behavior has been so well studied and understood that its use in various domains is becoming commonplace. This chapter provides an example of the use of the flocking ecosystem metaphor to the domain of productive efficiency analysis.

The use of associative inferences of flocking under a range of conditions was tested and has shown that a population of power plants can benefit by achieving higher and quicker levels of efficiency performance by adhering to the flocking factors both individually and in combination with other power plants in the population. As described in Section 5.8 above, it was discovered that there is also a number of limitations on the use of these inferences. It has been learned, for example, that as the adaptability level (i.e., 0,5,10,15,20,25), for the same flocking factor or combination of factors increases, the effect on PopMeanTE and PopMeanTTEF changes from very desirable to undesirable and even counterproductive. This research provides insights into the care that must be exercised, especially in the use of the flocking factors of separation distance and separation turn. Through this research it was found that each of the rules of flocking, taken individually, had the expected effect of increasing the collective efficiency of the population of power plants. It was also found that most combinations of the rules of flocking had the expected effect of increasing overall efficiency. It was found, however, that these effects were more limited than expected and were limited to a smaller than expected range of conditions where the levels of adaptability and to the flocking factors offer fewer option for attaining goals of increased technical efficiency and reduced time to achieve maximum efficiency.

5.10.2 Representing a DEA DMU as a CAS ABM Agent

This research concludes that a DEA DMU can be represented as a CAS ABM agent. In CAPEM a DEA ADMU is truly decoupled from the assumptions of the linear programming methodology. In this illustrative example it was demonstrated that CAPEM can represent a large number of ADMUs, can represent ADMU with it's own internal goals and rules and can model productive efficiency as a continuous dynamic representation.

CAPEM also decoupled the ADMU from the assumptions and constraints of the DPEM (Vaneman and Triantis, 2007) control-based system dynamics approach. By representing an ADMU in CAPEM as an independent, autonomous actor with its own set of goals, rules, etc., no top-down control is required, no collective goal needs be imposed on the individual ADMUs and no steady state or equilibrium needs be assumed. As has been demonstrated, patterns of collective behavior emerge without being imposed from the top-down as is appropriate to the representation of a real world ecosystem as opposed to the representation of a machine which requires the imposition of top-down physical laws. Through this illustrative example it has been shown that by providing ADMU with rules that have been found, in the natural world, to be successful CAPEM can offer insights and provide guidance for decision-making documented in this chapter, above.

5.10.3 Use of the DEA Production Possibility Space and the CAS ABM Environment

Recall that DPEM extends standard DEA by employing sets of interacting feedback loops in a classic control-theory systems approach. By continuously comparing the current state of system components of a single ADMU against a defined set of desired collective system goal states and by using this information to make appropriate adjustments in the use of system resources, a single decisionmaker could, over time, pursue policies that achieve significantly greater efficiencies than could be achieved by the standard snapshot in time step-wise form of DEA analysis. The CAPEM approach, as shown by this illustrative example, further extends the standard DEA approach by combining the notion of the standard DEA production possibility space with the DPEM notion of feedback loops. In place of the interacting feedback loops of system dynamics, CAPEM employs patterns of complex systems behavior that have been derived from analysis of the “perpetual novelty” (Holland, 1999, p. 4) that exists in the complex systems of nature. For the flocking metaphor used in this research the common purpose is mutual protection or what was defined in Chapter 3 as “hedging”. While at the same time autonomously pursuing individual goals akin to foraging for food or shelter power plants sought out the best use of fuel and labor. In CAPEM every interaction between autonomous power plants and every interaction between a power plant and the information available to it in the production possibility space is another valuable feedback loop. Without imposing top-down control, the interactions of a large number of feedback loops produce patterns of individual and collective behavior. Patterns emerge that are useful to decision-makers of both individual power plants (individual use of fuel, labor, production of electricity and time to the efficient frontier and individual technical efficiency) and the collective management level (PopMeanTE, PopMeanTTEF).

5.10.4 Use of the DEA Efficient Frontier and the DEA Definition of Technical Efficiency

In place of the unlimited flocking of autonomous entities to the point of convergence at a steady state as done in the most common representation of the flocking metaphor, the standard DEA notion of a common benchmark of efficiency, the standard DEA efficiency frontier, was substituted. By doing so CAPEM could employ the standard definition of technical efficiency used in DEA and employ it as a continuous function over time. Individual power plants could be seen to have a distance, in terms of relative efficiency, and direction, in terms of changes in policy over time, as compared to the efficiency frontier. Given the efficiency frontier as a benchmark the ADMUs in turn have a distance and direction as a compared to one another.

As a simplifying assumption for this research it was decided to employ in this illustrative example, a single instance of the standard DEA efficiency frontier computed at the beginning of the experiment. Doing so allowed us to focus on and observe in the simulation, the patterns of movement created by the decisions made by the power plants themselves. Updating the efficiency frontier at every new increment of time or at regular intervals could enrich the general understanding of the efficiency frontier as a foundational building block of DEA and the CAPEM approach.

5.10.5 Use of the CAS Notion of Adaptability

For CAPEM the flocking metaphor offers policy options, based on patterns of complex behavior that a population of power plants could pursue to achieve increased productive efficiency while at the same time gaining collective protection against making poor choices that would result in failure to achieve optimal productive efficiency. In this illustrative example, options take the form of the degree of adaptability a power plant possesses to adapt to the flocking factors. Alignment, cohesion and separation turn defined the basic options. The six levels of each of these factors used in the experiment (0,5,10,15,20,25) fixed the number of choices to a finite set options yet sufficient for these purposes. For this illustrative example this translates to the 1296 excursions of the experiment that define the full spectrum options available to adapt as the population of power plants seek individually to achieve maximum productive efficiency through minimizing the use of inputs. Within the limits of this illustrative example it has been determined that it is necessary for decision-makers to be selective of the options provided by this metaphor. As described in previous sections, options, particularly those related to separation turn (maintaining diversity) and separation distance (acceptable risk) may produce unfavorable results. Isolating options that would individually or collectively cause failure to progress toward optimal efficiency is equally valuable to the decision-makers. By sharing information the collective corporation is better able to maintain overall competitive advantage. While individual power plants may not always be maximally efficient at every increment, they will avoid catastrophic failure, surviving to eventually achieve optimal efficiency with the rest of the corporation.

5.10.6 Use of the DEA Production Function

In this research the production function was treated as another CAS ABM agent rule, one that may, in addition to the flocking rules, potentially influence power plant decision-making. Through this research the ability to incorporate the production function defined in the same form derived by Kopp (1981) and employed by DPEM (Vaneman and Triantis, 2007) was confirmed. This implementation of the PF unlike previous studies did not employ it as a driver of system behavior and therefore did not confound in any way an understanding of the factors of flocking on power plant decision-making. By comparison, it was concluded that the use of the production function in CAPEM, like its use in DPEM conforms to the standard DEA concepts/building blocks. By contrast DPEM employs the production function as an exogenous variable in its control-theory approach while in CAPEM the production function can be employed as an explicit, internal rule in each of the ADMUs.

5.11 Further Use of This Case Study

The concepts defined in this research and demonstrated by this illustrative example are exploratory intended to establish a foundation for an increasingly long list of meaningful next steps and future research. The immediate next step in this research is to be an investigation, using this same illustrative example, the impact of a dynamic efficient frontier updated at each increment of time or at meaningful regular increments of time. A second step is to make a comparison of results of executing the same experiment on a population of power plants whose starting condition are random. The Rungsuriyawiboon and Stefanou (2003) data used as the starting locations of the power plants in this experiment provided data on a population of power plants that were already marginally efficient. What it means to validate a CAS ABM simulation is still much in debate (Gilbert, 2008). Conducting field studies is highly desirable but may be years in the future. Conducting the experiment research against a randomly generated set of starting locations would likely provide more dramatic changes in the effects of the flocking factors and in the resulting estimators. Additional comparisons against the Rungsuriyawiboon and Stefanou (2003) data and comparison between the current experiment and an experiment conducted with randomly generated starting conditions may be the closest it is possible to achieve toward validation for the near future. Further examination of the relationship between PopMeanTE and PopMeanTTEF would be among these comparisons. One could then use the insights gained from these two steps to study the effects of the levels of adaptability to the four flocking factors individual power plants either against the historical data or the randomly generated starting conditions. Once this research is completed the greatest need for future research and the greatest desire of this researcher is to conduct field studies in an experiment designed for making comparisons and possibly validating the current research. Seeking an ability to validate the results of these findings researchers will be in search of management systems with whom a controlled field experiment may be conducted.

In the mid to long term, research is needed on ways to generalize this approach to other CAS ABM metaphors and other aspects of productive efficiency analysis. In this current research the productive efficiency counterparts to the flocking metaphor (hedging, best practices, maintaining diversity, avoiding competition among similar entities, level of risk) was examined. Metaphors related to the behavior of ants, cities and the human brain are currently being studied in great depth (Johnson, 2001) offering the opportunity to examine the concepts such as selforganization, development of clusters, cost-benefit analysis (disposability), transportation or supply chain flow, perceptions, human diversity, etc., as they might relate to productive efficiency. In the course of this research more advanced implementations of the flocking metaphor were discovered. Variations in the use of alternative subsets of the population of power plants were discovered, for example, to represent even more localized decision-making and alternative choices of flockmates with which to align or cohere. Variation from the use of straight line, radial measurement of location and TE in the PPS are already defined in both DEA and the CAS ABM literature (Tanner, 2001) and would offer a more refined means of examining productive efficiency. Also needed as soon as possible would be enhancements to our ability to employ more advanced and refined capabilities of CAS ABM. Work has already begun to incorporate 3-dimensional modeling and the use of fitness landscapes to represent variation in the CAPEM PPS into our current CAPEM NetLogo code (Ambler, Triantis and Dougherty, 2014).

Further refinement of the experiment would be needed to confirm such an observation. Recall also that the DEA efficient frontier is a relative, not an absolute benchmark and recall that the choice was made in this research to maintain the same EF throughout the experiment. The effect of a dynamic efficient frontier on the relationship between TE and TTEF may be great or small but worthy of near-term analysis. Note also that Rungsuriyawiboon and Stefanou (2003) included a population of power plants that had been in operation for a number of years? prior to being deregulated. While some level of inefficiency was inherent in highly regulated power plants all were relatively efficient as indicated by the starting locations of the 30 ADMUs in the experiment. Investigation into the effects of conducting the experiment with a larger less efficient population or even a randomly distributed population is strongly indicated.

6 Contribution to the Field, Generalization and Future Research

6.1 Contribution to the Field

Through this research a bridge between the DEA form of productive efficiency analysis and CAS ABM thinking and methods has been established. The intended contributions to the field of productive efficiency analysis of this research began with the identification of the relevant building blocks of DEA and the CAS ABM flocking metaphor. It has been shown in Chapter 1 that DMUs, the PPS, EF and PF are relevant building blocks of CAPEM as are CAS agents, rules, percepts and actions. Top-down central control is not. A contribution of this research to the field of productive efficiency analysis is the construction and description of the associative inferences made between the building blocks of DEA and CAS ABM. This research has shown that a DEA DMU can be well represented by a CAS agent. It has been demonstrated that a group of autonomous DEA DMUs driven by ecosystem based rules of alignment, cohesion and separation can represent a management system. And, it has been demonstrated that the collective behavior of DMUs interacting with one another according to these rules can result in patterns of behavior that lead to ever increasing levels of technical efficiency and offer policy options to real-world decision-makers that they had not previously considered.

To enable collaboration with the CAS ABM community a formulation of CAPEM has developed using Holland's Constrained Generating Procedure Notation, the language of emergence. CGP mechanisms have been formulated for the CAPEM simulation as a whole, for the user interface, the DMUs agents, the EF, the PPS and consistent with CGP notation, have specified the standardized descriptors for the sub-components of these mechanisms. Employing the coded transformation functions provided by NetLogo and supplementing them with functionality tailored for CAPEM an operational CAS ABM simulation was implemented. Using this simulation a full factorial design of experiment was conducted to examine the effects of the factors of flocking on the productive efficiency of a historically common DEA subject, a family of fuel-oil driven electrical power plants. Through this experiment it was shown that hands off management of 30 individual autonomous power plants each adhering to its own internals ecosystem-derived rules resulted in patterns of collective behavior that enabled the corporation as a whole to minimize inputs in a way that also increased the maximum relative technical efficiency and at the same time reduce the time required to do so. In the process of making these other contributions the conformity of CAPEM to the DEA axioms of production was confirmed and documented.

6.2 Generalization

To limit the scope of the research and to focus on assembling the foundational elements of future research on this effort, this research was deliberately constrained in a number of important ways. Releasing the following constraints will enable researchers and analysts to broaden the applicability of this research in a number of important ways.

6.2.1 Generalizing on the Building Blocks of DEA

Limiting ourselves to a single EF for the duration of a simulation excursion was the most important choice made early in the research. Doing so enabled a focus more on the behavior of the DMU and less on variations in the system environment. A dynamic EF would be akin to enabling the power plant DMUs to identify the most efficient power plant at each increment of time (monthly) and frequently update their efficiency benchmark to account for the very latest environmental conditions. Given the 14 year time horizon of the data in the experiments, the annual update of the EF or in power plant terms, an annual update of the efficiency PowerCorp efficiency benchmark, would be expected to add to the realism of the analysis and make a significant difference in the resulting TE over time. This is going to be especially true when taking into account rapid technological changes; In industries where the technology is not very mature, the EF could change continuously;

As described previously this research deliberately avoided the use of the DEA PF as a DMU rule. This was done to understand the influence of the CAS ABM emergence-based flocking factors (alignment, cohesion, separation) on DMU behaviors while doing so by monitoring the change in the inputs, the traditional factors of production (fuel and labor). Currently, as described in a previous section of this document DMUs guided by the flocking factors will often make decisions that cause them to temporarily move away from the EF. This is counterintuitive to traditional DEA productivity analysts but quite consistent with the ecosystem behaviors. It is challenging to anticipate the effects of inserting the PF in future research as an active DMU rule. Doing so would be mixing ecosystem defined rules and physics based rules. It is uncertain the combination would be interpreted. In context of the power plants it would be expected to limit DMU ecosystem driven decisions to only those choices that moved the DMU directly toward the EF in any single increment of time. It could be argued that this is more akin to the decision a human would make given the option. Having the option of being guided internally by either or both flocking factors and the DEA PF might be considered a violation of the flocking metaphor or it might be considered complementary but in either case it would be consistent with the building blocks of DEA. Implementing the DEA PF and the axioms of production explicitly as DMU internal rules could replace the flocking metaphor all together and is a viable alternative and would serve to better enable the comparison to existing systems dynamics models and broaden the applicability of CAPEM.

6.2.2 Generalizing on the Building Blocks of CAS ABM and the Flocking Metaphor

In this research numerous assumptions were intentionally simplified and therefore intentionally limiting the sophistication of the CAS ABM agents in CAPEM, the DMUs, and the interactions among them. The ability of a DMU to adapt was limited in each excursion of the simulation to a set of values for each of the flocking factors. The interaction between DMUs was limited to those defined by straight line distances between them with no change in the strength or intensity of the interactions as distances were decreased. In CGP terms these are fixed interactions. A spectrum of alternatives now exists to vastly increase a DMU's ability to learn and adapt and to therefore greatly broaden the range of applicability of CAPEM to other scenarios. Possibilities exist from simply refining the fidelity of the current set of CAPEM rules to implementing within the CAPEM simulation the most recent state of the art in agent-based attributes and reasoning (beliefs, desires, intentions, skills, aptitudes and the ability to change goals under specified conditions) (Bernon, Camps, Gleizes and Picard, 2003). CAPEM agentDMUs can be enhanced to sense fitness landscapes added to the current CAPEM environment (Ambler, Triantis and Dougherty, 2014).

Recent developments in CAS ABM have made it possible for DMUs to store alternative plans and when conditions are right, discard the current plan and replace it with a new one. In the power plant context this would be akin to being able to change, in any increment in time, which other DMUs it defines as its neighbor. Currently the DMUs define all other inefficient DMUs as its neighbor. Alternatively a DMU could be given the ability to look to only the closest 3-5 DMUs as its neighbors. If, for example, conditions became such that a DMU detected a sub-set of other DMUs whose use of fuel and labor was very similar to itself, this DMU could change its definition of neighbors. To be influenced by DMUs more like itself it could change its choice of neighbors from all inefficient DMUS to this sub-set. This is one of many possible changes than can be made to the internal rules of DMUs to increase the sophistication of the CAS ABM agents and broaden its applicability and use. In addition to increasing the sophistication of internal rules there are a range of ways to increase the sophistication of the interactions between DMUs.

Tanner, Jadbabaie and Pappas (2003) proved that the basic nature of the flocking behaviors was maintained even when the level of influence of one DMU over another changed with changes in the distance between them. In terms of the CGP notation this is a variable interface (Holland, 1999). The influence of neighboring DMUs could be increased, for example, as the differences in TE's between them decreased. The applicability of CAPEM to a broader set of problems would be greatly increased by expanding the ability to implement additional fixed and variable interfaces between DMUs.

6.2.3 Generalization to Other Ecosystem Metaphors

As previously described much of what is understood about emergent behaviors and solutions is determined through observation of natural phenomenon. Comparing man-made systems and organizational behavior to the behavior of ants, birds and fish, for example, has proven both insightful and practical. In Chapter 3 the associative inferences made to construct CAPEM were documented. Among the associations were the DEA DMU with an autonomous CAS ABM agent, the DEA PPS with the CAS ABM environment, the population of DMU with the PowerCorp management system and so on. These associations will persist regardless of the CAS metaphor. Unique to the flocking metaphor the flocking factor of alignment was associated with management system self-protective behaviors such as sharing mutual risks, hedging and other mutually protective strategies. The flocking factor of cohesion was associated with collaborative management system behaviors, such as sharing of best practices. The flocking metaphor is now so well accepted that it may soon lose its status as an emergent behavior (Johnson, 2001). It is becoming a commonly understood and accepted behavior and emergent properties are now being sought at the next higher level of aggregation. Gaining an understanding of behaviors and insights that emerge at the next level from flocking, such as patterns of combinations of factors will most often result in goal achievement, is the next logical step. At the same time numerous other CAS metaphors, foreaging by ants, synchronizing of illumination (communications) among fireflies and swarming by crickets, termites and slim mold have begun to receive significant attention.

Replacing the flocking metaphor with other metaphors and associating them with other management system behaviors would greatly expand the applicability of CAPEM. Termite behaviors have been associated with the behaviors of populations in crisis conditions (Fisher, 2009). Inserting a pillar or other round object in the midst of a swarm of fleeing termites results in patterns of behavior that improved the ability of the swarm to achieve safety. This metaphor has been used successfully to redesign emergency exits from modern buildings. Employing the same metaphor and making appropriate associations to either a physical or conceptual pillar may lead to insights about management systems in crisis. The behavior of so called Mormon crickets, who in 1848 swarmed and nearly devoured the crops of the struggling Mormon settlers to the Salt Lake valley, have been associated with the behaviors of collective trust and mutual motivation (Fisher, 2009). When food is plentiful these crickets forage individually. As sources of food become increasingly scarce, they begin to aggregate and swarm together toward other sources of food while maintaining a certain separation from one another. If resources become desperately scarce, the separation distance is lost and they begin to devour one another. Besides the obvious, partly humorous association of this emergent swarming behavior with corporate management system behaviors, additional research showed that it was the effort of individual crickets attempting to flee from cannibalism that caused the swarming, each cricket trying to get out in front of the other.

Using CAPEM, a productive efficiency analyst, employing the cannibal cricket metaphor and by making appropriate associations to management system could offer behavioral, transactional and policy insights that to this point may not have been considered. This research shows that such associations and practical applications of CAS ABM are increasing. A review over time of the NetLogo model library of biologically based models readily indicates this trend (Wilensky, 1999). Fostered by Northwestern University research and a large open NetLogo user community such metaphors are being examined from a number of perspectives similar to what was done in this research. CAPEM can be readily adopted to any number of CAS ecosystem metaphors greatly expanding its applicability. Within the NetLogo model library alone there are numerous simulations that have been validated for thire representation of a variety of ecosystem metaphors (Wilensky, 1999). An ant colony ecosystem simulation can be used to represent marketing or a search for system resources of other kinds. Though each ant or market development resource follows a set of simple rules, the colony or management system as a whole acts in a sophisticated way. Another model simulates the behavior of a population of fireflies as they synchronize their flashing using only the interactions between individual fireflies. It is a good example of how a distributed system with numerous interacting components can coordinate itself without any central coordinator (Wilensky, 1999).

6.3 Future Research into the Use of CAS for Analysis of Productive Efficiency

Beyond increasing the sophistication and generalizing on the methods and tools described in this research, the primary thrust of this future research will be to conduct field experiments using CAPEM. It is essential that a link be made between this simulation based experimentation and the real world experimentation. The meaning of "validation" in the context of CAS ABM is not well understood (Gilbert, 2008). As was described in Chapter 4, the CAPEM case study, comparisons can be made in terms of aggregate results but matching curves over time between systems dynamics based models and physics-based factors of production oriented DEA decision-making and CAS ABM ecosystem metaphors based decision-making but the comparison is indirect at best. CAS ABM and ecosystem metaphors have been applied to decision-making in healthcare (Kernick, 2002), manufacturing (Nilsson and Darley, 2006), economics (Beinhocker, 2006), sociology (Sawyer, 2005) and to other disciplines. Nowhere in literature search for this research was there found an instance of a direct application of CAS ABM to the DEA form of productive efficiency analysis. This research begins to take the opportunity to do so. Having now established the foundational building blocks, associative inferences and mathematical formulations, the goal for future research will be to identify a specific real world, DEA appropriate application of CAPEM and conduct appropriate fieldbased research. Organizations, public or private, will be identified, in which, hedging, use of best practices and or diversity are key factors in decision-making and whose decision-makers can are sufficiently open minded enough to adopt or experiment with ecosystem metaphors as a means of determining policy. Future research need not be constrained to the flocking metaphor but this metaphor would remain among the first consider if appropriate. Sawyer (2005) cited above, for example, has a well-articulated framework for what he calls the “Emergence Paradigm of Sociology” (Sawyer, 2005, p.189). Sawyer is a strong advocate of applying CAS ABM ecosystem-based approaches to a new, more rigorous definition of the field of sociology as a whole. Now that the foundational associations between productive efficiency analysis and CAS ABM has been made CAPEM should be considered to engage with one or more of these disciplines in the real world particularly the disciplines sociology and economics.

A second major direction of future research for us would be to conduct experiments specifically designed to isolate and characterize the level of emergence above flocking. As stated previously an existing validated CAS metaphor, flocking was applied to create the bridge between paradigms and through the case study to exercise the ability in this research to gain management system insights from CAPEM. The next level of rigor in this regard would be to attempt to isolate patterns of flocking behavior that with high likelihood will lead to would lead increasing individual and collective TE and reduce time to achieve maximum efficiency. Through this research the hypothesis was confirmed that increasing levels of adaptability for each flocking factor or combination of factors could provide decision-makers with one or more options for achieve these goals. In this first step it was confirmed that CAPEM could generate such options. The next step in this research is to determine the confidence with which these options can be made, test the boundaries of their validity. Ultimately this kind of research is attempting to find an eloquent equation describing the pattern of behavior for the flocking metaphor that would serve as a proxy to always employing the metaphor itself. In other words such research is attempting to find the behavior that in context of productive efficiency will emerge above or beyond flocking. So just as CAPEM used equations and code for alignment, cohesion and separation, future research is looking for equations and code that describe the patterns of behavior that emerge from applying what is already known about flocking. Once these equations are found they could be leveraged or applied appropriately to inform and assist management system decision-makers with greater efficiency and insight than is now provided by the flocking metaphor.

A third direction for future research would be to determine and document the value of a hybrid CAS ABM and SDM method of analysis. Now that both dynamic methods exist research into combining the value of top-down, control-theory based approach with the bottom-up, complexity science based approach may prove valuable. Several tools such as NetLogo (Wilensky, 1999) and AnyLogic (AnyLogic, 2014) now offer both forms of programing in a single platform One study conducted jointly between MIT and the MITRE Corporation (Love and Mathieu, 2007) employed the SDM to represent the continuous operation of a management system and employed CAS ABM to represent periodic meetings of a decision-making board. Policy-guidance derived by the board was applied over time to the continuous operation of the management system. Applying this foundational research directly to such a paradigm would be to assert the value of the DEA form of efficiency analysis and the flocking factors to this management system. Employing CAPEM more generally would be to assert the value of a range of DEA building blocks and CAS metaphors as indicated by the specific needs of the analysis.

A fourth direction of future research would be to establish an even more solid connection to the theory and research underlying DEA. There are a number of other building blocks of DEA, such as allocative (cost) and overall efficiency, disposability, and numerous alternative forms of DEA, not addressed in this research that could and should be experimented upon and incorporated into CAPEM. DEA is a very powerful, well respected analytic tool in its own right. The research and accompanying empirical data provide a rich source of comparative studies not only for comparison alone but also for the purpose of being persuasive in attracting management system decision-makers to its use. The “theory of the firm” which has a long history (Berle and Means, 1937; Hendersen and Quandt, 1980), provides a useful basis for the representation of the management system used in this research and for future research. The axioms of production, which concisely articulate the fundamental application of physics-abased thinking are widely accepted and remain valid. Enhancing the comparability between these and CAS ABM paradigm would attract the existing DEA community to CAS ABM in a way that would benefit everyone. Engaging these communities in a widespread collaboration would more rapidly advance knowledge and new insights in both domains.

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Appendix A Summary Descriptions of the CAPEM NetLogo-Based Code

A.1 The NetLogo Agent-Based Simulation

As stated in the NetLogo user's guide, NetLogo is a programmable modeling environment for simulating natural and social phenomena. It was authored by Uri Wilensky (1999) and has been in continuous development ever since at the Center for Connected Learning and Computer-Based Modeling. NetLogo is particularly well suited for modeling complex systems developing over time. Modelers can give instructions to hundreds or thousands of "agents" all operating independently, making it possible to explore the connection between the micro-level behavior of individuals and the macro-level patterns that emerge from the interaction of many individuals.

NetLogo enables the analyst to open a range of simulations on a wide variety of CAS metaphor simulations and explore their behavior under various conditions. It is also an authoring environment that enables students, teachers and curriculum developers to create their own models. NetLogo is simple enough that students and teachers can easily run simulations or even build their own. And, it is advanced enough to serve as a powerful tool for researchers in many fields. NetLogo is the next generation of the series of multi-agent modeling languages that started with StarLogo. It builds off the functionality of StarLogoT, adds significant new features and a redesigned language and user interface. NetLogo runs on the Java virtual machine, so it works on all major platforms (Mac, Windows, Linux, et al.). It is run as a standalone application, or from the command line. Models and HubNet activities can be run as Java applets in a web browser.

A.1.1 NetLogo Syntax

The following explanations of the NetLogo code are provided in the spirit of John

Holland's (1999) observation that computer simulation will enable us to understand emergence at its most elemental level. Understanding the NetLogo code at this level is in many instances, the best way to understand how emergence arose from the combined building blocks of CAS and productive efficiency.

Some initial tips about the syntax of NetLogo that might make understanding the code easier:

- Any block that begins with a reserved word "to" is a procedure. The word "to" is followed by the name of the procedure. The body of the procedure is enclosed between "to" and "end"
- Any block that starts with "to-report" is again a procedure whose name is followed by the key word to-report. This procedure returns a value to the calling procedure. The Value is returned by using the keyword "report."

The lines of code that are in bold are those taken from the original NetLogo Flocking Model and those line that are not in bold were written for the purpose of this research.

A.1.2 Tailored Procedures – Defining the Environment and Initialization of Agents

Flocking formulations assume a common coordinate space and scale in which all agents can operate.

A.1.2.1 Declaration of Global Variables

```
globals
[
 initial-number-of-admus  minimum-
separation  max-separate-turn  sorted-ef
]
```

We are declaring variables that may be used later in the code. These variables are visible throughout the code. A number of global variables were defined in the code to complement the buttons and slider bar provided in the user interface. Doing so will significantly facilitate large numbers of runs that are expected in experimentation using the simulation.

A.1.2.2 Differentiating Efficient from Inefficient Agent DMUs

```
breed [inefficient-admus inefficient-admu] breed
[efficient-admus efficient-admu]
```

The term "admu" here means "agent decision-making units." The turtles in the model are divided into two breeds: efficient DMUs and inefficient DMUs. Standard NetLogo "turtles" are of one kind or breed. To accommodate the distinctly different behaviors between efficient and inefficient DMU is was necessary to define a second breed of turtles or agents.

A.1.2.3 Properties of Agents (turtles, inefficient DMUs, efficient DMUs)

```
Turtles-own
[
 Heading-from-origin
 Tech-efficiency
]
```

The above lines of code set properties for each turtle in the model. These properties can be accessed by the NetLogo procedures that monitor the turtles and cause them to simulate as desired. Here "heading-from-origin" is the angle made by the line joining the turtle and the origin with the zero axis (the y-axis in NetLogo case). Technical efficiency, which will be explained in detail in later sections, is also a variable that has a unique value for every turtle depending upon its distance from the Efficient Frontier. These two properties are common to all the turtles - both efficient ones and inefficient ones.

```
Inefficient-admus-own
[
 peers
flockmates
nearest-neighbor
]
```

The variables "peers", "flockmates" and "nearest neighbor" are properties associated only with the in-efficient DMUs. The inefficient DMUs lose these properties once they reach the efficient frontier and become efficient. The values for these variables will be set at a later point of time. Standard NetLogo “turtles” own, or in other words, can identify flockmates and nearest-neighbors. To accommodate the DEA concept of peers, Inefficient DMU may now also own “peers”.

NetLogo defines a common coordinate space in which each agent DMU, known in NetLogo terminology as a “turtle” is aware of some number of nearby agents, known as its neighbors or in the flocking metaphor, its flockmates. The number of neighbors of which an agent can be aware can be set manually by the analyst or be defined actively in the simulation. Each agent DMU can determine the distance to each neighbor and can therefore determine its nearest neighbor, which is essential in the flocking behaviors.

A.1.2.4 Initial Setup of the Agent DMUs

The “to setup” which is the procedure to do the initial setup, is linked to a user button named “setup” in the user interface of the flocking model. When the user clicks on the setup button, this procedure is executed.

```
to setup-admus
```

```
create-inefficient-admus Initial-Number-of-DMUs
;;Initial-Number-of-DMUs is the value from the slider



if (Own-Seed != "System-chosen-seed") [     random-
seed Own-Seed
]

ask inefficient-admus
[
  set color white        set shape "house"        set size 1        setxy (random
max-pxcor) (random max-pycor) ;; to avoid the admus being placed in negative
co-ordinates of x and y
]
calculate-heading-from-origin     set-current-
plot "Technical Efficiency Plot" end
```

Prior to starting a simulation run we can chose to place the agent DMUs randomly throughout the coordinate space or provide an input file with coordinates for each agent DMU. We then identify the efficient DMU and create the EF. Those agent DMU that are not on the EF are inefficient and as stated previously are treated as a different breed of agents. Once identified we, through this procedure, we give them their graphical characteristics and calculate their initial heading from the origin.

The number of DMUs to be created is decided by the user. The DMUs created are given a particular color, shape and size. The positioning of the DMUs is random. The user allows the system to select a random seed to produce a totally random pattern of distribution of DMUs or can choose a seed himself to generate a specific pattern every time. In the above code snippet we are also telling NetLogo to use the “Technical Efficiency Plot" graph to do the plotting on.

A.1.3 Tailored Procedures – Agent Movement Over Time

The NetLogo flocking variable for velocity (distance over time) is defined as the distance an agent DMU must travel in an increment of time to achieve the combined effects or influences of the flocking factors. The movement of agent DMUs over time is a key building block in the flocking metaphor and representations of complex adaptive productive efficiency.

NetLogo provides for the basic animation and movement of agent DMUs through the "to go" procedure, below. This procedure is linked to the user button named "go" in the user interface of the flocking model. When the user clicks on the go button, this procedure is executed.

A.1.3.1 The "to go" Procedure

```
to go
  if
  (count inefficient-admus = 0)
  [
   stop
  ]
  if  (count inefficient-admus = 1)
and
  (
    ([xcor] of (one-of inefficient-admus) = 0)
and
    ([ycor] of (one-of inefficient-admus) = 0)
    )   [
stop
  ]
  ask inefficient-admus
  [
     ifelse goal-reached? [make-efficient self] [flock]
```

```
  ]
  ;; the following line is used to make the turtles
;; animate more smoothly.   repeat 5 [      ask
inefficient-admus
     [         fd 0.2         set
xcor max list 0 xcor         set
ycor max list 0 ycor;]
       ] display
     ]
  ;; for greater efficiency, at the expense of smooth
;; animation, substitute the following line instead:
  ;; ask turtles [ fd 1 ]

 calculate-heading-from-origin

  ;;The below lines print the Tech Efficiency
  ;;of every inefficient DMU to the Console
  ;; in every tick
   print "---------------
"   print "tick : "
  print ticks   print "-
--------------"
  show-tech-efficiency
  tick

  ;; to update the graph after every tick
update-plot end
```

The "ask-inefficient-admus" function calls the "flock" parameter. By doing so, each agent DMU queries the environment to determine the identity its flockmates. In the standard NetLogo model, agent DMUs identifies flockmates as those agents that are within a minimum distance, defined by the analyst. It is this set of agent

DMUs that are used to compute the primary flocking formulations: alignment, cohesion, and separation.

The “repeat 5” function divides the “patch” into five increments, displaying the agent DMU five times for every unit of simulation time. The unit of simulation distance in NetLogo is a “patch.” The unit of simulation time is a “tick.” The more the patch is divided the smoother the motion but also the slower the simulation. Reducing the number of changes in display per unit of time increases simulation efficiency but makes the display appear jagged.

The distance an agent DMU can “go” or move for each time step is determined by the rate of change of the real world situation and must be matched to the number of patches an agent DMU can or should move in a tick of time. Time steps in NetLogo can be set to match real world increments of time or if needed by the analyst the time step can be some fraction of the scenario/real world increments of time.

The introduction of the DEA Efficient Frontier (EF) concept into flocking behaviors required significant modification to the procedure. Recall that in DEA, efficient agent DMU actually define the Efficient Frontier and need not move. Those not on the EF are inefficient. The modified “ask turtles”, is “ask inefficient-admu” which only queries these inefficient DMU to establish its “flock”.

As inefficient DMUs reach the EF they become efficient and must no longer be included in the movement calculation. This is represented in our modified code with an “ifelse” statement. Before each move the inefficient DMU asks itself if it has reached the goal. Here goal is the Efficient Frontier. "goal-reached?" is a procedure that returns true if the inefficient DMU has reached the EF else it returns false. Depending upon the value returned by "goal-reached?" the DMU decides whether to stop flocking or continue flocking. "calculate-heading-from-origin" is a call to a function that sets the property 'heading-from-origin" of every turtle to the angle the turtle makes with the zero-axis. The line "show-technical-efficiency" prints the Tech Efficiency of every inefficient DMU to the Console in every tick. The line "updateplot" calls a function to continue plotting the graph for every tick.

A.1.3.2 The “to flock” Procedure

```
to flock   find-
flockmates   if any?
flockmates
   [
     find-nearest-neighbor       ifelse distance nearest-neighbor <
Minimum-Separation-Distance
        [
          separate
        ]        [
align
cohere
        ]
      ]
End
```

This procedure is at the heart of the flocking simulation. To flock an agent DMU first finds its flockmates using the “find-flockmates.” If there are flockmates the agent DMU then finds its nearest neighbor using the “find-nearest-neighbor” function. If the nearest neighbor is within a minimum separation distance, the agent DMU immediately attempts to separate itself to avoid a collision. Given what the agent DMU now knows about its flockmates and nearest neighbors it performs the three primary flocking behaviors, “separate”, “align” and “cohere”, in that order.

A.1.3.3 The “to find-flockmates” Procedure

```
to find-flockmates   set
flockmates other turtles end
```

This procedure enables the turtle to find its flockmates. In the original model the agents identified flockmates as those within a set radius. To incorporate the DEA Reference Set concept, this procedure was changed to include all agent DMUs other than itself.

A.1.3.4 The "to find-nearest-neighbor" Procedure

```
to find-nearest-neighbor ;; turtle procedure   set nearest-
neighbor min-one-of flockmates [distance myself] end
```

Among all the flockmates of a turtle, the one that is closest to the turtle is set as its nearest-neighbor.

A.1.3.5 The "to turn-at-most" Procedure

```
;; turn right by "turn" degrees (or left if "turn" is negative),
;; but never turn more than "max-turn" degrees to
turn-at-most [turn max-turn]  ;; turtle procedure
ifelse abs turn > max-turn
   [ ifelse turn > 0
       [ rt max-turn ]
       [ lt max-turn ] ]
   [ rt turn ]
end
```

This procedure is used by both "turn-away" and "turn-towards" procedures. It requires two parameters namely, "turn" and "max-turn". The max-turn is set by the user.

If the absolute value of "turn" is greater than "max-turn" the agent DMU will be limited to the max-turn. If "turn" is greater than "max turn" and greater than zero (positive) then turn right by “max-turn”, otherwise turn left by the “max turn”. If the absolute value of turn is less than “max-turn” turn left or right by that amount. The value of the parameter (turn) used by the procedure is computed in two ways. First, when this procedure (to turn-at-most) is called by the "to turn-away" procedure, turn is assigned a value equal to the difference between the heading and the new-heading, in that order. Second, when this procedure (to turn-at-most) is called by the "to turntowards" procedure, turn is assigned a value equal to the difference between the newheading and heading, in that order.

A.1.3.6 The “to turn-away” Procedure

```
to turn-away [new-heading max-turn]  ;; turtle procedure   turn-at-
most (subtract-headings heading new-heading) max-turn end
```

This “to turn-away” procedure is called by the "separate" procedure and enables the agent DMU to turn to avoid a collision with its nearest neighbor(s).The first parameter is the difference between heading and new-heading which is the result of the function "subtract-headings" The second parameter is the max-turn that determines the maximum turning angle that the turtle can take. Just as with the align and cohere procedures, the agent DMUs ability to separate is limited by the “to turnat-most” procedure. Recall that the “to separate” procedure takes priority over the “to align” and “to-cohere procedures.

A.1.3.7 The “to turn-towards” Procedure

```
to turn-towards [new-heading max-turn]  ;; turtle procedure   turn-at-
most (subtract-headings new-heading heading) max-turn end
```

This procedure is called by both the “align” and “cohere” procedures. Based on the two parameters “new-heading” and “max-turn” an agent DMU turns toward a flockmate to align with the general direction of the flock and/or to cohere with selected flockmates. NetLogo defines right and left turns in degrees from its current heading. The new-heading parameter is determined by the "to turn-at-most" procedure, described below. The max-turn parameter is determined set by the user.

A.1.4 Tailored Procedures for Alignment, Cohesion, Separation A.1.4.1 Alignment

Alignment is defined as the direction and distance an agent DMU takes to match the average heading of all agent DMU in the flock. At each increment of time an agent DMU will attempt again to align with the average direction and velocity of its flockmates. NetLogo will compute a "turn-towards average-flockmate-heading".

The "average-flockmate-heading" corresponds to "alpha" in the flocking formulations.

A.1.4.1.1 The "to align" Procedure

```
to align  ;; turtle procedure   turn-towards average-flockmate-heading
Maximum-Alignment-Turn ;slider end
```

This procedure is called from inside the "to flock" procedure, explained above. This procedure causes the agent DMU to "turn-towards" the "average-flockmateheading" or the "Maximum-Alignment-Turn" whichever is smaller. The "Maximum-Alignment-Turn" is set by the user using a slider bar on the user interface.

A.1.4.1.2 The "to-report average-flockmate-heading" Procedure

```
to-report average-flockmate-heading
  ;; We can't just average the heading variables here.
;; For example, the average of 1 and 359 should be 0,
;; not 180.  So we have to use trigonometry.
```

```
  let x-component sum [sin heading-from-origin] of flockmates
 let y-component sum [cos heading-from-origin] of flockmates
 ifelse x-component = 0 and y-component = 0
   [report heading-from-origin]
   [ report atan x-component y-component ] end
```

These procedures are calculations that return the value of the average heading of all flockmates from the origin. Trigonometry is used to make these calculations to overcome limitations of averaging angles that may sum beyond 3600. It is this average heading of all flockmates to which an agent DMU will seek to align itself. Note also the accommodation made to incorporate the DEA concept of technical efficiency, which is calculated as distances between the origin and the EF. The original NetLogo flocking code calculated new headings from an agent DMUs current heading.

The result of the calculation is an x and y component for a vector whose origin is the origin and that passes through the current location of the agent DMU. Note also that the x-component is calculated using the "sin" function and the y-component is calculated using the "cos" function which is opposite standard trigonometry functions. This is an artifact of the NetLogo base code that employs this convention for reasons that we have not yet determined.

If x-component and y-component are both equal to zero, then return the current heading of the turtle. Otherwise return the arc- tangent of x-component and ycomponent, which is the new heading of the agent DMU would take to achieve alignment.

A.1.4.2 Cohesion

Cohesion is defined as the direction and distance an agent DMU takes to move toward a point on the EF that is the midpoint between the two closest efficient agent

DMUs, known as its peers. In contrast to the alignment vector, which is a collective measure (average-flockmate-heading), the cohesion vector is determined by the (average-heading-towards-peers). An agent DMU will continuously seek to cohere individually to each of a selected subset of its neighbors as opposed to seeking to “align” with the average heading of the other agent DMUs.

NetLogo determines the direction needed to maintain cohesion by computing a “average-heading-towards-flockmates”. Note this is not “average-flockmateheading” as in alignment, but an “average-heading-towards-flockmates”. The turn is not toward the average of the headings of its flockmates but to the mean of the angles between the agent DMU and each of its flockmates individually. This is the essential difference between alignment and cohesion.

A.1.4.2.1 The “to cohere” Procedure

```
to cohere   turn-towards average-heading-towards-peers Maximum-
Cohere-Angle end
```

This procedure is likewise called from inside the "flock" procedure, explained above. It causes the agent DMU to "turn-towards" the "average-heading-towardspeers" or the “Maximum-Cohere-Angle” whichever is smaller. Note another DEA accommodation, this time for the DEA concept of the “peer set”, which are the two efficient DMU on the EF that define the point of optimal efficiency for the sub-set of inefficient DMU whose heading from the origin passes between these two efficient DMU. This is in stark contrast to the original NetLogo code, which calculates the “average-heading-towards-flockmates” using all flockmates. The procedure that enables an inefficient DMU to identify its DEA peers is defined below.

A.1.4.2.2 The “to identify-peers” Procedure

```
to identify-peers
ask inefficient-DMU
  [
     set peers  min-n-of 2 efficient-DMU [distance myself]
  ]
end
```

Peers are the two closes efficient DMUs to any of the inefficient DMUs. The above procedure lets each inefficient DMUs identify their peers. This is an accommodation to DEA that enables the inefficient DMUs to seek the appropriate place on the EF.

A.1.4.2.3 The “to-report average-heading-towards-peers” Procedure

```
to-report
average-heading-towards-peers

  ;; "towards myself" gives us the heading from the other turtle
  ;; to me, but we want the heading from me to the other turtle,
  ;; so we add 180

  ifelse count efficient-admus > 2
  [ set peers  min-n-of 2 efficient-admus [distance myself] ]
  [ set peers efficient-admus]   let x-component mean [sin
(towards myself + 180)] of peers   let y-component mean [cos
(towards myself + 180)] of peers   ifelse x-component = 0
and y-component = 0
    [report heading-from-origin]
    [ report atan x-component y-component ] end
```

This procedure is a calculation that returns the mean of the heading of the DEA peers. Trigonometry is used to make these calculations in order to overcome limitations of averaging angles that may sum beyond 360^0.

A.1.4.3 Separation

More general flocking concepts define separation as the distance an agent DMU seeks to maintain from its flockmates to avoid a collision. To explicitly articulate separation NetLogo is looking for a “turn-away ([heading] of nearest-neighbor) max-separate-turn” in degrees. No trigonometric transformations are required. The code simply employees functions that have already been calculated and the helping procedure “to turn-away”. “Max-separate-turn” is an analyst defined parameter.

A.1.4.3.1 The “to separate” Procedure

```
to separate  ;; turtle procedure   turn-away ([heading] of nearest-
neighbor) Maximum-Separation-Angle end
```

This procedure is likewise is called from inside the "to-flock" procedure. It calls another procedure "turn-away" with two parameters. The first parameter is the heading of the nearest-neighbor and the second parameter is the “Maximum-Separation-Angle”. The "Maximum-Separation-Angle" parameter is another variable that is set by the user before the start of the simulation using a slider bar in the user interface.

A.1.5 New Procedures Needed to Enable Unique DEA/DPEM Concepts and Facilitate Experimentation A.1.5.1 The Efficient Frontier Procedures

Probably the most notable change in the approach to flocking needed to accommodate DEA concepts of productive efficiency is the concept of the Efficient Frontier. The standard NetLogo concept of flocking, indeed the commonly accepted concept of flocking, is continuous iterative flocking movement toward potential convergence of a number of flocks into a single converged flock. The approach we have taken is to employ the flocking behaviors for convergence onto an EF. Metaphorically it is like a flock of birds choosing collectively to land on a set of power lines. Defining the efficient frontier and rationalizing the flocking behaviors with the DEA concepts in a single simulation required the definition of a series of new procedures as follows:

A.1.5.1.1 The "to draw-ef" Procedure

```
to draw-ef   set sorted-ef sort-by [before ?1 ?2]
efficient-admus    let y [ycor] of first sorted-ef   ask
first sorted-ef
  [
    hatch-efficient-admus 1
     [
       set pen-size 3
pen-down         setxy
0 y
       ;; This hatched turtle does not die because it
       ;;serves as an artificially created efficient
       ;; DMU on the Y-axis
     ]
  ]
  ask first sorted-ef
[ hatch 1
  [
    set pen-size 3     pen-down
foreach but-first sorted-ef       [ move-
to ?  set color [color] of ? ]     die
  ]
]

let x [xcor] of last sorted-ef ask
last sorted-ef
[
 hatch-efficient-admus 1
  [
```

```
    set pen-size 3
pen-down      setxy
x 0
    ;; This hatched turtle does not die because it
    ;;serves as an artificially created efficient
    ;; DMU on the X-axis
  ]
]
set sorted-ef sort-by [before ?1 ?2] efficient-admus
;;The final EF includes 2 artificial turtles on x and y axis into the sorted list end
```

The approach we took to identify the EF is captured in this procedure. It implements the DEA axioms of production described in section 3 above. Consistent with the convexity axiom, the EF for an output maximization problem contains the upper-most and right-most agent DMUs in this coordinate space as well as the respective x and y intercepts from those points. The first upper-most and right-most agent DMU are located simply by finding those agent DMU with the greatest x and y coordinates. Consistent with the Closedness and Boundedness axioms the EF for an output maximization problem contains a finite set of agent DMU bounded by the remaining, most efficient agent DMUs.

To identify subsequent upper-most and right-most agent DMU we created a search pattern of ever-decreasing triangles whose hypotenuse is formed by a line drawn between the current upper-most, right-most pair and whose other two sides are parallel to the axes. The next upper-most and right-most agent DMU pair are located by moving this line outward with the same slope. When located, the next upper-most and right-most are labeled as efficient and the next search begins. When the upper-most agent DMU is also the right-most DMU the search stops.

This procedure is used to draw the EF using the NetLogo "pen-down" option for drawing lines. The "pen-down" option is a NetLogo facility that allows the display of smooth lines of various widths to replace the more jagged line of white patches. This procedure includes 2 artificial turtles on x and y axis in the sorted list of efficient agent DMU that form the EF.

A.1.5.2 The "to-report find-upper-most [temp-turtles]" and "to-report findright-most [temp-turtles]" Procedures

```
to-report find-upper-most [temp-turtles]
report temp-turtles with-max [ycor]  end

to-report find-right-most [temp-turtles]
report   temp-turtles   with-max   [xcor]
end
```

These procedures are supplemental calculation to support the "to identify-EF" procedure. It creates a temp-turtle entity that is used to calculate and report the agent DMUs with the maximum x and y coordinates.

A.1.5.3 The "to make-efficient [temp-DMU]" Procedure

```
to make-efficient [temp-admus]
ask temp-admus
  [
    set breed efficient-admus
set shape "house"     set
color red     set size 2
    set tech-efficiency 1
  ]
end
```

Once identified as an efficient, by the “to identify EF-new” procedure, an agent DMU must be given a new breed and new appearance in the simulation display. This procedure accomplishes these changes.

A.1.5.4 The “to find-efficient-DMU [u-most r-most]” Procedure

```
to find-efficient-admus [u-most r-most]
let xu [xcor] of u-most   let yu [ycor] of
u-most


  let xr [xcor] of r-most
  let yr [ycor] of r-most


  let temp-turtles turtles-in-triangle (first xu) (first yu) (first xr) (first yr)
let number count temp-turtles
```

This procedure is a supplemental calculation to support the “to-identify EF-new” procedure. The ever-decreasing triangle approach was effective until the number of agent DMU in the triangle fell to two or below. Having 0, 1 or 2 agent DMUs in the latest triangle requires treatment as a special case. This procedures counts the number of agent DMU remaining in the latest triangle.

```
 ;; Case 1   if
number = 0
  [
   make-efficient u-most
make-efficient r-most    stop
  ]
```

If zero agent DMUs remain in the triangle, the most recent upper-most and rightmost agent are efficient and define the EF. This and the “to identify EF-new” procedure stops.

```
  ;; Case 2   if
(number = 1)
  [
    make-efficient temp-turtles
stop
  ]
```

If one agent DMU remains in the triangle, it is defined as efficient and along with the most recent upper-most and right-most agent are efficient and define the EF. If so, this and the “to identify EF-new” procedure stops.

```
    ;; Case 3   if
(number = 2)
  [
    let temp-u-most find-upper-most temp-turtles
let temp-r-most find-right-most temp-turtles

    let right-most-u-most find-right-most temp-u-most     make-
efficient right-most-u-most

    let upper-most-r-most find-upper-most temp-r-most     make-
efficient  upper-most-r-most

    stop
  ]
```

If two agent DMUs remain in the triangle, the algorithm checks for the uppermost and the right-most among them. If upper-most itself is the right-most too, only that one is made efficient. Otherwise both are made efficient. If two agent DMUs remain in the triangle the problem is a bit harder. One or both may be in the EF. When a line are drawn between the current upper-most agent DMU and each of the 2 remaining agent DMUs and a line is drawn between the current right-most agent DMU and the two remaining agent DMUs, four line segments are formed. The line segment with the least slope will be in the EF and the line segment with the greatest slope will also be in the EF. The other two line segments will not. This procedure resolves that dilemma.

```
  ;; Case 4   if
number > 2
 [
  let temp-u-most find-upper-most temp-turtles
let temp-r-most find-right-most temp-turtles    let
right-most-u-most find-right-most temp-u-most
let upper-most-r-most find-upper-most temp-r-
most

  ifelse right-most-u-most = upper-most-r-most
  [
    make-efficient right-most-u-most
stop
  ]
  ;else part
  [
    ;;RECURSIVE CALL      make-efficient right-most-u-most
make-efficient upper-most-r-most      find-efficient-admus
right-most-u-most upper-most-r-most
  ]
]
end
```

Having more than two agent DMUs in the triangle is the normal case. The uppermost and rightmost of the three is identified and made efficient and the next search begins.

A.1.5.5 The “to-report turtles-in-triangle [xu yu xr yr]” Procedure

```
to-report turtles-in-triangle [xu yu xr yr]
let m ((yr - yu) / (xr - xu))     let c (yu -
(m * xu))

   report inefficient-admus with
   [
     (xcor > xu) and (xcor < xr) and (ycor > yr) and (ycor < yu) and
 (ycor >= (m * xcor + c ))
   ]   end
```

This procedure identifies the agent DMUs in the current triangle. It does so by first calculating the slope of the line between the current upper-most and current right-most agent DMU and then calculating c, the y-intercept. If an agent DMU has an x and y coordinate that are beyond this line it is in the triangle. Other procedures, described above, are used to determine which of the remaining agent DMUs are on the EF.

A.1.5.6 The "to-report left-most [temp-turtles]" Procedure

```
;; This procedure returns the turtles with
;; least x-coordinate among the temp-turtles agent set
to-report left-most [temp-turtles]   report min-one-of
temp-turtles [xcor] end
```

A.1.5.7 The "to-report bottom-most [temp-turtles]" Procedure

```
;; This procedure returns the turtles with
;; least y-coordinate among the temp-turtles agent set
to-report bottom-most [temp-turtles]   report min-one-
of temp-turtles [ycor] end
```

The use of upper-most and right-most agent DMUs to identify the EF are appropriate for output maximization problems. As described in section 3 above, this is only one of the two primary types of DEA productive efficiency problems. To enable use of these same methods for input minimization problems it is necessary to identify the EF using left-most and the lower-most agent DMUs. This procedure and the following procedure allow for this occurrence.

A.1.5.8 The "to-report before [temp1 temp2]" Procedure

```
to-report before [temp1 temp2]
report [xcor] of temp1 < [xcor] of temp2 or
([xcor] of temp1 = [xcor] of temp2 and
[ycor] of temp1 > [ycor] of temp2) end
```

This procedure returns true if turtle temp1 has a lesser x-cor than turtle temp2 or an x-coordinate equal to that of Turtle temp2 But return False if the x-cor of temp1 is greater than that of temp2. This procedure is used to sort the efficient turtles in ascending order of their x-coordinates.

A.1.5.9 The "to-report goal-reached?" Procedure

```
to-report goal-reached?


  let x  precision ([xcor] of self) 2 ;; reducing the precision helps catch most of the
turtles that cross EF.
  let y  precision ([ycor] of self) 2


  (foreach (but-last sorted-ef) (but-first sorted-ef)
  [
   let x1 precision ([xcor] of ?1) 2
let y1  precision ([ycor] of ?1) 2
```

```
  let x2 precision ([xcor] of ?2) 2
let y2  precision ([ycor] of ?2) 2

  if (( round x >= x1) and ( round x <=  x2)); round x here is good for vertical lines
  [
    ifelse (x1 != x2)
    [
      let m precision ((y2 - y1) / (x2 - x1)) 2
let c precision (y1 - ( m * x1)) 2

      ;; All these conditions are necessary!
      if y =  precision ((m * x) + c) 2           or (round y = (m *
x) + c)             or (y = (m * round x) + c)            or (round y
= (m * round x) + round c)            or round y = round( (m * x
) + c) ; very good condition           or round y = round ( (m *
round x) + c)            or round y = round ( ( m * x) + (c + 1))
or round y = round ( ( m * x ) + ( c + 2))           or round y =
round ( ( m * x ) + ( c + 3))           or round y = round ( ( m *
x ) + ( c + 5))           or round y = round ( ( m * x ) + ( c + 4))
or round y = round ( ( (m + 1) * x ) + ( c ) )
         or round y = round ( ( (m + 2) * x ) + ( c + 1 ) )
      [report true]
    ]
    [
      if (( round y <= y1) and ( round y >= y2)) ; to deal with division by zero
[report true]
    ]
  ]
  ]
 ) ;end of foreach
report false  end
```

For an agent DMU to reach the EF is a major milestone in the DEA calculations of productive efficiency. Reaching a goal is also a key concept in CAS. To implement this concept in the simulation we define the EF mathematically as a line with a slope and intercept. At the end of each move we ask each agent DMU to determine if it has reached the line/EF. This procedure does so and makes the information available for use in other procedures.

The coordinates of turtles in NetLogo are of very high precision. With that precision it is impossible for the turtle's coordinates to satisfy the equations of line segments that make the EF. In order to better capture the turtles that reach the EF we have used many conditions that involve rounding off the coordinates to the nearest whole number and reducing the precision to only two while checking for the conditions etc. These are simple conditions with very little variation of the actual equation but they are powerful in terms of capturing the DMUs that have reached the goal. However, when the number of DMUs is very large, NetLogo fails to capture all the DMUs on the EF. This is the only major pitfall in this version of the model and it can be resolved with some effort in the future versions.

A.1.5.10 The "to calculate-headings-from-origin" Procedure

```
to calculate-heading-from-origin
ask turtles
 [
   ifelse (xcor = 0) and (ycor = 0)
   [
    set heading-from-origin 0
   ]
   [
     set heading-from-origin 90 - (atan xcor ycor)
   ]
 ]
```

```
end
```

This procedure defines an agent DMUs heading from the origin for use by the simulation and the analyst.

In addition to having a position on the coordinate space (the productive efficiency space) that represents its relative efficiency, each agent DMU has a heading. This is analogous to each agent DMU having a policy direction that decision-makers believe will increase the efficiency of their system or organization. One approach to defining a heading for each agent DMU is to set this heading randomly at the beginning of the simulation. A second approach is to assume some level of knowledge of the environment, specifically, the EF and assume that the policy direction is always facing toward the EF from the origin.

A.2 The Value of Using NetLogo in This Research

As stated in section 4 above, NetLogo is a modeling environment for simulating natural and social phenomena. It was authored by Uri Wilensky in 1999 and has been in continuous development ever since at the Center for Connected Learning and Computer-Based Modeling. NetLogo is particularly well suited for modeling complex systems developing over time. It is specifically designed as an agent-based simulation. Modelers can give instructions to tens or hundreds or thousands of "agents" all operating independently, making it possible to explore the connection between the micro-level behavior of individuals and the macro-level patterns that emerge from the interaction of many individuals.

NetLogo enables the analyst to open a range of simulations on a wide variety of CAS metaphor simulations and explore their behavior under various conditions. It is also an authoring environment, which enables students, teachers and curriculum developers to create their own models. NetLogo is simple enough that students and teachers can easily run simulations or even build their own. And, it is advanced enough to serve as a powerful tool for researchers in many fields. NetLogo runs on the Java virtual machine, so it works on all major platforms (Mac, Windows, Linux, et al). It is run as a standalone application, or from the command line. Models and HubNet activities can be run as Java applets in a web browser.

A.2.1 Strengths for Use in This Research

Even before deciding on the research hypothesis NetLogo was useful as a hub for literature search. NetLogo provides a library of both validated and invalidated agentbased models representing the fields of art, biology, mathematics, chemistry, physics, games, earth science and social science. Designed for both instruction and research, it provides an excellent start point for locating CAS metaphors, which can be compared, contrasted and possibly matched to the research domain. Our choice of the flocking metaphor was strengthened by descriptions provided in the model library and by the ready reference to the validated code provided there. Any researcher seeking for candidate emergent behaviors to explain their research domain would do well start in the NetLogo model library. Doing so is a bit like curve fitting in more traditional forms of analysis.

A second strength of the NetLogo simulation is the relative simplicity of the development environment. It straightforwardly supports the fundamental elements of agent-based modeling, i.e., the agent environment, creation of agents themselves, agent rules, percepts and actions and the communication (percepts, actions) among them. The programmer uses a relatively simple procedural language to take advantage of the agent-based features embedded in the underlying foundation of the simulation. The NetLogo simulation is very well documented and has a very active user community. Both of these were very helpful in this research where the simulation was not the focus of the research or the primary skill of the researchers.

The main advantage of NetLogo was that is permitted us to modify the basic code to accommodate the unique aspects of the productive efficiency research domain. Creation within NetLogo, of the EF and differentiation between efficient and inefficient agent DMU, while at the same time maintaining the integrity of the basic flocking procedures, is key to the research. Being able to simulate the fundamental building blocks of standard productive efficiency analysis and the fundamental building blocks of complex adaptive systems thinking enabled us to produce a dynamic, non-linear approach to analysis of productive efficiency. The building of a running simulation that enables agents to independently align with the DEA reference set, cohere with the DEA peer set and separate sufficiently to account for data inaccuracies is on its face supportive of the hypothesis. Experimentation and analysis of simulation results are expected to provide additional evidence in support of the hypothesis. Use of CAS metaphor is distinctly different from using a system of differential equations representing system or organizational components. Use of the NetLogo simulation allowed for comparisons of inputs, outputs and capture of DEA technical efficiency over time as a measure of productive efficiency.

Clearly the simulation supports a readily repeatable process of experimentation. A sub-hypotheses of the research asserts that emergence of patterns necessary to increase program performance will arise from this effort by less efficient DMU to move toward the efficient frontier. Furthermore it is the expectation of this author that this emergent behavior will metaphorically resemble the flocking behavior of birds as they land, collectively, on a set of power lines. While “in flight” the DMU follow rules that determine their distance from one another and the direction at which they need to move to “land” on the power line as near as possible to other birds.

Unlike field studies, the NetLogo simulation allows analysts to experiment with a very large number of agent DMU and program factors, modeled as agents. The interaction of many agents (DMU) following simple rules (DEA), when properly modeled in agent based simulations, create patterns. These patterns are the signs of emergence, patterns of self-organizing local system or organizational behaviors that arise from a large number of very simple goals, rules, percepts and actions. While easy to understand individually their combination creates complexity and dynamics that the human mind cannot grasp as a whole. Fortunately, these patterns can be detected and analyzed in an agent-based model and can be shown empirically to forecast program behavior. Properly modeled in agent-based modeling CAS analysis can discern the patterns that emerge from interaction of these factors (agents) over time and can lead to very useful leading indicators of program behavior.

It is useful to distinguish three forms of emergent structures. A first-order emergent structure occurs as a result of shape interactions (for example, hydrogen bonds in water molecules lead to surface tension). A second-order emergent structure involves shape interactions played out sequentially over time (for example, changing atmospheric conditions as a snowflake falls to the ground build upon and alter its form). Finally, a third-order emergent structure is a consequence of shape, time, and heritable instructions. For example, an organism's genetic code sets boundary conditions on the interaction of biological systems in space and time. All three order of emergent are supported in NetLogo, The representation of simple rules and behaviors of individual agents is well supported in NetLogo as is the secondorder interaction among agents as defined by the alignment, cohesion and separation flocking behaviors. It is the third order emergent behavior that we seek to discern using the simulation. Data capture capabilities and the analysis tools, especially the visualization displays provided by NetLogo are very helpful in this aspect of the research.

A.2.2 Weaknesses for Use in This Research

From the perspective of this research, there were very few weaknesses of NetLogo. Java programmers may find the procedural code somewhat limiting. Because this simulation was relatively simple, however, it was not often necessary to use the power of more powerful, elegant programing languages. A capable JAVA programmer has all the skill necessary to quickly learn and adapt to the NetLogo language.

From a non-programmer perspective it was sometimes challenging to understand the code when it called a function or parameter that was designed into the NetLogo platform and not made explicit in the procedures. This is true for all languages but might be considered a weakness for a language that claims to useful by novices and students.

The coordinates of the patches in NetLogo are whole numbers and the coordinates of the turtles are decimal numbers with high precision. This causes a slight problem during the simulation. Also the lines drawn on the model are on a layer above the turtle and the patch layer. Hence, there is no way for the turtle to directly detect when it crosses a line. These two factors together pose a great challenge to capture all the turtles that reach the EF. After adding many conditions to the code we were able to achieve the capturing of almost all the turtles that become efficient. However, when the number of turtles is high, even the algorithm fails to capture all the turtles, which results in some of them leaking out of the EF. A little more effort is required to dig up a better solution for this problem.

A.2.3 Next Steps

This is the very first attempt to represent the combined building blocks of CAS and DEA productive efficiency in a simulation. At the time of this writing the results have not yet been analyzed nor have any variations on the scenario been attempted.

One this analysis has been conducted a better assessment can be made of NetLogo's ability to support this type of analysis.

The essential next step is to verifying that simulation is performing as expected. The current face verification is very encouraging but it will be necessary now to examine the data for expected simulation outputs and outcomes. We intend to focus on the data captured for an examination of DEA technical efficiency. This will involve a tick by tick examination of the positions and headings for each agent DMU for the entire period of the simulation. Further it will involve examination of the agent communication to ensure that each agent was communicating with the appropriate reference set or peer set throughout the simulation and that the appropriate distances between agents was used in the calculation of technical efficiency.

Once the model has been verified the next step will be too seek means of model validation. We will first compare model results with an established DEA illustrative example, the "power plant" scenario first published by Schmidt and Lovell in 1979 and to the DPEM results produced by Vaneman-Triantis in 2007 for the same scenario. Validation using other scenarios and real world data is beyond the scope of this research nit will be actively pursued. The NetLogo display has provided a degree of face validation that is hopeful but requires true validation.

Anticipated longer-range next steps include extending the simulation to enable examination of multiple isoquant and isocost solutions. This will involve the ability to change agent goals over time and will require the generation of multiple EF over time. Adding cost as a factor will be a significant next step and will enable the evaluation of isocost curves so essential to the analysis of DEA allocative efficiency and the evaluation of the disposability of inputs and outputs over time.

Consider will be given at some point to moving to a more sophisticated simulation and modeling language such as Repast J that will enable programmers to employ the power of Java and other more efficient object-oriented languages and take advantage of more capable goal-seeking and learning behaviors that have been developed by the agent-based modeling community. For now however, NetLogo is quite satisfactory and is actually preferred for its simplicity and usability.

Appendix B Satisfying the Axioms of Production in CAPEM

B.1 The Importance of Satisfying the Axioms of Production

Economists have long sought a mathematical approach to the description and analysis of units of production (firms) and the factors of productivity themselves. Graig and Harris (1973) explained the importance of measuring total rather than partial productivity. Hendersen and Quandt (1980) provided a microeconomic "theory of the firm" with mathematical models. More recently Färe and Primont (1995) provided an axiomatic set of properties that explain and govern the activities of a production environment. This set of axioms are representative of any condition found where inputs are converted into outputs and provide a starting point from which assumptions about production systems can be made. Not all axioms apply to all circumstances but satisfaction of those axioms that apply is a necessary condition for validity of analytic methods such as DEA, DPEM and CAPEM.

B.2 The Axioms of Production

Underlying DEA is the "theory of the firm" (Graig and Harris, 1973; Hendersen and Quandt, 1980). Included in this theory are the axioms of production, which concisely articulates the fundamental patterns of production. These axioms are building blocks of DEA. A CAS representation of efficiency should initially conform to the axioms or have a well-articulated purpose for relaxing the axiom. The axioms of production are:

- Axiom 1, (No Outputs) it must be possible for the system to produce zero outputs even when inputs are provided.
- Axiom 2, (No Free Lunch), outputs can never be produced in the absence of inputs.

- Axiom 3, (Free Disposability), it must always be possible to produce the same level of output even if the levels of input vary.
- Axiom 4, (Scarcity), the level of outputs that can be produced is limited or bounded. Finite inputs can only yield finite outputs.
- Axiom 5, (Closedness), it is possible to produce only positive real numbered amounts of outputs with only the positive real numbered amounts of input.
- Axiom 6, (Convexity) If a series of inputs x_i can produce y, then any weighted combination of x_i can produce y.

B.3 Conformance to the DEA Axioms of Production

DEA are further formalized for CAPEM in the context of the axioms of production. Definitions of the axioms of production originate with Fare and Primont, (1995). The following are basic notations used for discussion of the axioms of production.

B.3.1 Axiom 1a, the Productive Inactivity Axiom:

The inactivity axiom says that a model of productive efficiency must be able to represent a situation where a system can at any time produce no outputs even in the presence of inputs. The CAPEM form of this axiom follows:

Table B-1. Inactivity Axiom

Agent Based Representation	Axiom 1a – Inactivity
$0 \in T(x), \forall x \in \Re^{N}{}_{+}$	It is possible to produce no outputs

The CAPEM modeling environment directly adheres to this axiom by enforcing the origin at zero and constraining the environment to positive values along a given coordinate scale. The absence of an input or the presence of an input in no way prohibits an output value of zero.

Figure B-1. Inactivity Axiom

The “inactivity axiom” states that it is always possible to produce no outputs. That is, even if inputs are introduced into the system it is possible that these inputs will produce zero outputs. Using our illustrative scenario as an example, if fuel and labor are input to the production process it is possible that zero electrical power is produced. A static system whose inputs produce no outputs would simply remain a rest with no production. A dynamic system would remain in its current state, either at rest or in its current state of equilibrium. There would be no production or no change in its current level of production, respectively. The dynamic/DPEM model of this axiom is stated as:

Dynamic Axiom1a. $0_t \in P(x_{t\text{-}to}; y_{td\text{-}to})\ ,\forall\ (x_{t\text{-}to}; y_{t\text{-}to}) \in \Re^N_+$

To satisfy the “inactivity axiom” the CAPEM CAS flocking environment (the productivity space) was defined to include all non-negative results and therefore the possibility of either producing zero output given zero or a very small positive amount of input. Through experimentation it was observed that agentDMUs did, in fact, achieve a zero productivity value for some period of time. It was also observed that some agentDMU after achieving a zero productivity value, would either remain at zero or recover and return to a positive productive efficiency consistent with the dynamic model of the axiom. Some of the latter category of agentDMUs would eventually even achieve a state of maximum productivity.

In addition to the CAPEM productivity space being set up to allow for inactivity, the agentDMU rules (i.e., the NetLogo flocking equations) enabled a result/solution of zero output or zero change in output during a time increment. While adhering to the flocking rules it is always possible for the combination of flocking influences on any one agentDMU to either be zero or remain constant during a increment in time. Consequently is always possible for an agentDMU to choose a policy that leads, at least for a time, to less efficiency and possibly even to inactivity for the duration of the simulation. By seeking to follow the same general direction of other similar agentDMUs and by simultaneously seeking to cohere with the most efficient agentDMU (peer set) and at the same seeking to maintain the desired separation direction and distance from it closest neighbor, an agentDMU could choose not to move at all or not to change from its current state during a time increment. CAPEM therefore satisfies Axiom 1(a), the inactivity axiom.

B.3.2 Axiom 1b, the No Free Lunch Axiom

The no free lunch axiom ensures that the model does not allow for the production of outputs in the absence of inputs. The CAPEM form of the axiom is:

Table B-2. No Free Lunch Axiom

Agent Based Representation	Axiom 1b – No Free Lunch
$y \notin T(x=0), if\ y > 0$	No outputs in the absence of inputs.

In the CAPEM implementation ADMUs operate in the space formed by the technology possibility set. As illustrated in Figure B-1, it requires the addition of inputs for the ADMUs to move away from the origin toward the EF that bounds the space. The CAPEM environment directly implements this axiom, as illustrated in Figure B-1 above, by incorporating the origin and the axis of the coordinate scale that defines the production possibility space. Any time the inputs are zero, there are no outputs.

Axiom 1(b), the "no free lunch" axiom, further amplifies Axiom 1(a). This axiom is known as the "no free lunch" axiom (Färe and Primont, 1995) because it states that it is not possible to produce outputs or stay at a current state of equilibrium at time t, in the absence of inputs during an interval of time, $[t_0, t]$. A static system with no inputs would obviously produce no outputs and would simply remain a rest with no production. A dynamic system with no inputs during an interval of time would remain in its current state of equilibrium be it at a state of rest or in its current state of equilibrium. Axiom 1(b) is represented dynamically as:

Dynamic Axiom 1b. $y_t \notin P(x_{t-to}; y_{td-to}) = 0$, if $y_t > 0$

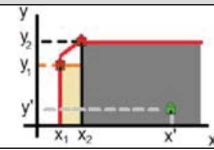
To satisfy the "no free lunch axiom" the CAPEM CAS flocking environment (the productivity space) and the agentDMU rules include the mathematical possibility of having zero inputs and with zero inputs there are no other possible results than zero outputs. This was borne out in the results of the simulation. As the simulation progressed it was observed that any time there were zero inputs there was no change in the current state of the system during that time interval.

If in the NetLogo flocking equations there were no input during a increment in time the value of each of the influence vectors on each agentDMU would be zero. With all influence vectors being zero there would no change to the current direction or velocity of an agentDMU. CAPEM therefore satisfies Axiom 1(a), the inactivity axiom.

B.3.3 Axiom 2, Free Disposability of Inputs and Outputs

It is always possible for DMUs to produce in a less efficient manner. As described in section III, in the CAPEM model, rules are incorporated into each ADMUs that define the degree to which a decision-maker is free to substitute one technical factor of production for another in order to align and more closely adhere with their local peer set.

Table B-3. Disposability Axioms

Agent-Based Representation	Axioms 2a&b - Free Disposability of Outputs and Inputs
$(x, y) \in T, x' \geq x, y' \leq y$ $\Rightarrow (x', y') \in T$	It is always possible to produce fewer outputs given more inputs. 

In the case of the flocking metaphor, the ADMUs flocking movements occur in the technology possibility set. This technology possibility set is a compact set formed through the scarcity axiom and closedness axiom, discussed below, and it contains all possible production possibilities. This compact set, along with the convexity restriction when identifying the efficient frontier, ensures appropriate disposability. The converse of this relationship exists in the case of an input model.

The second production axiom is also separated into two parts. Axiom 2(a), the weak input disposability (a.k.a., little input slack or strong input proportionality) axiom states that if all inputs are increased proportionally, outputs will not decrease. If inputs are not increased proportionally, outputs may decrease (Färe and Primont, 1995). Thus if output y_t is produced by input $x_{t\text{-}t0}$, an output jy_t can also be produced by input $x_{t\text{-}t0}$, when $jy_t = y_t$. A static system with weak input disposability (strong proportionality) would be easily controlled and have little slack or waste as a result of changes in input. A dynamic system with weak input disposability would be easily controlled and would have little slack or waste during each time interval. The dynamic weak output disposability axiom is represented as:

Dynamic Axiom 2a.

$$\text{If } y_t \in P(x_{t-to}; y_{td-to}) \wedge \lambda \geq 1 \Rightarrow y_t \in P(\lambda x_{t-to}; y_{td-to})$$

Standard DEA has confirmed that any agentDMU that lies on the efficient frontier has weak input disposability/strong proportionality. The weighting/proportionality of each input can be determined by measuring the distance from the agentDMU to each of its peer set on the efficient frontier. It is for this reason that we use the radial projection of an inefficient agentDMU onto the efficient frontier as a means of calculating technical efficiency. We measure the input disposability, "slack" or non-proportionality of an inefficient agentDMU by measuring the difference between the current distance from the inefficient agentDMU to its peers and the distance from the same agentDMU projected onto the efficient frontier and its peers. Output will not decrease for agentDMUs on the efficient frontier of an input-minimization problem. Output of agentDMUs not on the efficient frontier (inefficient agentDMU) will decease because inputs do not change proportionally over time.

By adhering to the DEA concepts/building blocks of the efficient frontier and peer sets, CAPEM incorporates this DEA axiom into the NetLogo simulation. Proportionality corresponds, in CAPEM, to the degree of alignment, cohesion or separation. In input-minimization scenarios, greater alignment (a smaller alignment angle) corresponds to weaker disposability of inputs or greater proportionality of inputs with respect to the reference set. Likewise, greater cohesion (a smaller cohesion angle) corresponds to weaker disposability or stronger proportionality with the peer set. Likewise for the separation angle and separation distance from an agentDMUs nearest neighbor.

It is possible to have opposite disposability relationships between reference, peer sets and nearest neighbors. It is conceivable for an agentDMU, for example, to choose to align loosely with the general direction of the population of other agentDMUs in their industry while choosing to cohere closely with the industry leaders, especially when the industry leaders may be doing markedly better than the general population, while at the same time maintaining a very minimal separation from its nearest neighbor. A power plant agentDMU, for example, will move/adapt more quickly the more sensitive they are to changes in the cost burden. The more sensitive a power plant is to the decisions of its reference set, peer set or nearest neighbor the less input disposability it displays. CAPEM therefore satisfies Axiom 2(a), the weak input disposability axiom.

Axiom 2(b), the strong input disposability (a.k.a., lots of input slack or weak proportionality) axiom, states that if any input increases, whether proportional or not, output will not decrease (Färe and Grosskopf, 1996). A static system with strong input disposability (weak proportionality) be able to varying the inputs significantly without decreasing the output. Changes to input would have less, possibly no, effect on outputs. A dynamic system with strong input disposability would be able to varying inputs significantly during each interval of time without decreasing output. In a dynamic environment, if increases to $x_{t\text{-}t0}$ during the time horizon $[t_0, t]$ are only weakly proportional or not proportional at all, the output y_t , at the corresponding time period t will be less effected or not effected at all.

Dynamic Axiom 2b.

$$\text{If } y_t \in P(\breve{x}_{t\text{-}to}; y_{td\text{-}to}) \wedge x_{t\text{-}to} \geq \breve{x}_{t\text{-}to} \Rightarrow y_t \in P(x_{t\text{-}to}; y_{td\text{-}to})$$

In CAPEM, strong input disposability corresponds to an increased angle of alignment, cohesion or separation and a greater separation distance being selected by the modeler. Experimentation bears out this relationship. Greater angles of alignment, cohesion and separation resulted in longer response times and longer overall time to converge/achieve maximum efficiency. CAPEM therefore satisfies Axiom 2(b), the strong input disposability axiom.

The third production axiom is also separated into two parts. Axiom 3(a), the weak output disposability (little output slack) (strong output proportionality) axiom states that a proportional reduction of outputs is possible (Färe and Primont, 1995). The utility of this axiom is most commonly found when the system produces both desirable and undesirable outputs (e.g., consequences of pollution regulations) (Färe and Grosskopf, 1996). If this axiom is applicable, then in order reduce the undesirable output(s), the desirable output(s) must also be reduced by the same proportional amount (Färe and Primont, 1995). Thus if output y_t is produced by input x_{t-t0}, an output □y_t can also be produced by input x_{t-t0} , when □$y_t \leq y_t$. The dynamic form of the weak output disposability axiom is represented as:

Dynamic Axiom 3a.

$$y_t \in P(x_{t-to}; y_{td-to}) \wedge 0 \leq \varphi \leq 1 \Rightarrow \varphi y_t \in P(x_{t-to}; y_{td-to})$$

In output-maximization scenarios, greater alignment (a smaller alignment angle) corresponds to weaker disposability of outputs or greater proportionality of outputs with respect to the reference set. Likewise, greater cohesion (a smaller cohesion angle) corresponds to weaker disposability or stronger proportionality of outputs with the peer set. Likewise for the separation angle and separation distance from an agentDMUs nearest neighbor.

Axiom 3(b), the strong or free (meaning lots of and cheap) output disposability axiom, states that some outputs can be disposed of without cost. The cause of this condition may be an inefficient production process that generates waste that can be discarded without consequences (e.g., smoke from a production process being emitted to the environment can be considered a costless disposal of an undesirable output in the absence of pollution regulations) (Färe and Grosskopf, 1996). In a dynamic system, production processes during the interval [t0, t] may yield outputs that are disposed of without costs, if and only if at least one output variable is exogenous to the system. Otherwise, they will create feedbacks into the system endogenously that will have performance consequences. Dynamic Axiom 3(b) is represented by: Dynamic Axiom 3b.

$$y_t \in P(x_{t-to}; y_{td-to}) \wedge \breve{y}_t \leq y_t \Rightarrow \breve{y}_t \in P(x_{t-to}; y_{td-to})$$

In output maximization scenarios in CAPEM, strong output disposability corresponds to an increased angle of alignment, cohesion or separation and a greater separation distance being selected by the modeler. Experimentation bears out this relationship. Greater angles of alignment, cohesion and separation resulted in longer response times and longer overall time to converge/achieve maximum efficiency. CAPEM therefore satisfies Axiom 2(b), the strong output disposability axiom.

B.3.4 Axiom 4, Scarcity of Inputs and Outputs

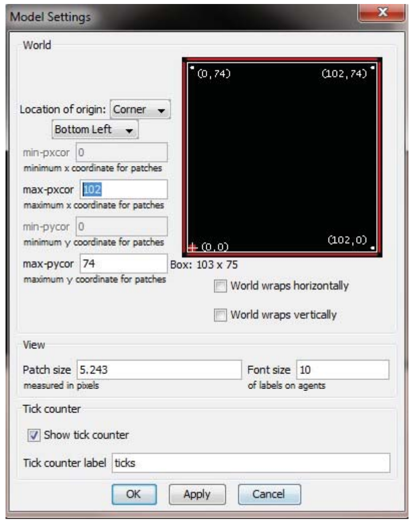
Scarcity (or Boundedness) requires that in any model of productive efficiency finite inputs can yield only finite outputs. The CAPEM form of the axiom is:

Table B-4. Scarcity of Inputs and Outputs Axiom

Agent Based Representation	Axiom 4 - Scarcity
$\forall x \in \Re^N{}_+, T(x)$ $is\ a\ bounded\ set$	Outputs are bounded; therefore, finite inputs can only yield finite outputs.

In CAPEM the environment is bounded by the limits of the possibility space which the modeling environment bounds. The bounds can be further defined by the user. Figure B-2 (Wilensky, 1999), depicts these global model settings in NetLogo model settings that enforce the limits of the production probability space.

Figure B-2. Finite Limits of the Model Environment



Axiom 4, the “scarcity” axiom states that finite amounts of input can only yield finite amounts of output (Färe and Primont, 1995). To satisfy the scarcity axiom the set of possible outputs must be bounded; they must be limited or in a manner of speaking they must be scarce. Without trivializing this definition it simply says that all the inputs and outputs being considered in our scenarios must be finite. First, the amount of input is finite and is bounded by some actual upper and lower bound. Second, a finite input cannot magically produce limitless outputs. In a dynamic environment, the inputs are also bounded within the time domain. Thus bounded resources within [t0, t] can only yield finite outputs at corresponding time t. The dynamic definition for DPEM is represented by:

Dynamic Axiom 4.

$$\forall x_{\text{t-to}} \in \Re_{+}^{N},\ y_t \in P(x_{\text{t-to}}; y_{td\text{-}to}) \text{ is a bounded set}$$

By definition all inputs and outputs in the CAPEM environment are finite. The definition is the true for all increments of time. Inputs are limited to only nonnegative amounts. There is no possibility in the CAPEM implementation of flocking behaviors that any single input or any combined set of inputs (i.e., labor, fuel, and/or capital) would result in production of an unlimited amount of electrical power. The same is true for all increments of time. CAPEM satisfies the "scarcity" axiom of production.

B.3.5 Axiom 5, Closedness

Similar to before, closedness bounds the feasible region of production. This is accomplished by limiting the model to production to real values along the positive horizontal and vertical axes. These axes have global coordinate maximums, guaranteeing closedness of the set for the simulation by limiting the space where ADMUs can randomly spawn (in turn limiting the construction of the EF). The CAPEM form of this axiom is:

Table B-5. Closedness Axiom

Agent Based Representation	Axiom 5 - Closedness
$\forall x \in \Re^{N}{}_{+}, T(x)$ $is\ a\ closed\ set$	Given the output y as a series of vectors $y_j = (y_1, y_2, \ldots y_m)$ such that the $\lim_{j \to \infty} y_j = y$; if every sequence of outputs y_j can be produced from inputs x_i then x can produce y.

In CAPEM, just as in standard DEA, the efficient frontier is constructed by identifying the ADMUs that are most efficient. Because these efficient points are themselves included in the range of possible inputs and outputs the productivity space is said to be not only "bounded" but "closed" as well.

Axiom 5, the "closedness" axiom, simply says that the set of possible inputs and outputs include those at the limits of the bounded set. Given that output y is a series of vectors, $y_j = (y_1, y_2, y_3,...y_m)$ such that lim y_j as j approaches infinity equals y_j. If every sequence of output vectors y_j can be produced from inputs x_i, then x can produce y (Färe and Primont, 1995).

In the dynamic form of the axiom developed in DPEM, if the inputs x at time tt_0 can produce every sequence of vectors yj at time t, then x_{t-t0} can produce y_t. DA.5 is shown as:

Dynamic Axiom 5.

$$\forall\, x_{t\text{-}to} \in \Re^N_{+},\ y_{\,t} \in P(x_{t\text{-}to};\, y_{t\text{-}to}) \text{ is a closed set}$$

In CAPEM, just as in standard DEA, EF is constructed by mathematically identifying the agentDMU that are most efficient with respect to each of the factors of production and then ensuring they are also most efficient with the combination of factors. Because they are themselves included in the range of possible inputs and outputs the productivity space is said to be not only “bounded” but “closed” as well. Additionally, the ends of the line segments that make up the EF closest to the x and y axis are extended to the respective axis to enclose the productive possibility set. As a result, the productivity space is bounded and by including these extreme points in the range of possible solutions it is also closed. CAPEM satisfies the “closedness” axiom of production.

B.3.6 Axiom 6, Convexity

All points in the production possibility set must be a convex set. For example, if a series of inputs x_i can produce an output y than a weighted combination of these inputs can also produce y. The CAPEM form of this axiom is:

Table B-6. Convexity Axiom

Agent Based Representation	Axiom 6 - Convexity

$\forall(x, y) \in T, 0 \leq \lambda \leq 1 \Rightarrow \lambda(x_i, y_i) + (1-\lambda)(x_{i+1}, y_{i+1}) \in T$	A convex set is the result of a weighted combination of two extreme points; this combination yields a line segment that joins the two points. If a series of inputs x_i can produce y, then any weighted combination of x_i can produce y.

In the CAPEM model convexity is achieved by creating EF that are concave to the origin in the case of output maximization problems and convex to the origin in the case of input minimization problems. The model ensures that ADMUs can only occupy production possibility sets that represent a weighted combination of inputs and its outputs. Adherence to this axiom may not or may be necessary since the calculation of efficiency does not utilize linear programming techniques nor does it currently follow from any parametric form with unequal weights. Whether or not it is required CAPEM provides the ability to adhere to this axiom should it be necessary.

The convexity axiom (Färe and Primont, 1995), states that all points in the productivity space (all combinations of inputs and outputs) must be calculable as a weighted combination of any two points (including the extreme points) in the productivity space. The weighted combination yields a line segment that joins the two points (Hillier and Lieberman, 1995). Thus if x_i and x_j are both a series of inputs that can produce y, then any weighted combination of x_i and x_j can produce y.

In a dynamic form of the equation developed in DPEM, x_i and xj can be inputs during different times within the time interval $[t_0, t]$ as long as their respective outputs share common time period t. DA.6 is described as:

Dynamic Axiom 6.

$$\forall\ x_{t-t_o} \in S(y_t) \in \Re^N_+ \ if\ 0 \leq \lambda \leq 1 \Rightarrow \lambda\,(x_{t-t_o}; y_{td-t_o}) + (1-\lambda)(\breve{x}_{\tau-\tau 0}; y_{td-t_o}) \in S(y_t)$$

The CAPEM implementation of NetLogo flocking behavior conform to this axiom. The approach to “cohesion” employs the peer set of a given agentDMU as the extreme points in each increment of time. AgentDMUs cannot move anywhere that would not result in a combination of inputs and outputs whose weights to not sum to 1. With respect to our illustrative example, decision-makers at any given power plant can only chose among production policy options that employ a weighted combination of fuel, labor or capital in proportions that sum to one, in any one time increment. CAPEM satisfied the “convexity” axiom of production.

B.4 Implications for CAS Analysis of Productive Efficiency

Combining the building blocks of both productivity analysis with CAS flocking behaviors has never been done before. Demonstrating conformity to the fundamental building blocks of productivity analysis, the axioms of production, provides the CAPEM NetLogo simulation with a means of validation, greatly increasing its credibility with those who subscribe to this form of analysis. Conformity to the axioms assures productivity analysts that the CAPEM approach to analysis incorporates known patterns of productive behavior.

Conformity to the “inactivity” axiom, for example, assures productivity analysts that the CAPEM approach to analysis incorporates situations when combining certain inputs results in inactivity (no production of desired outputs). Once analysts accept CAPEM as a valid representation of fundamental patterns of production they become open to the whole new spectrum of insights provided from a whole new perspective. Thinking of decision-makers as “birds of a feather” and accepting that their decisions follow patterns initially observed in flocks of birds or swarms of fish provides analysts with a new way of thinking of productivity and a spectrum of entirely new insights.

The fundamental purpose for birds flocking and fish swarming is protection from predators. Comparison could be readily made with the standard risk analysis and planning done by organizational decision-makers. By “aligning” with the general direction of its industry in terms major investment decisions an organization "protects" itself from making decisions, which if they fail, will be considered embarrassing or fundamentally unsound. "Cohering" to acknowledged industry leaders provides guidance, which, in the absence of having personal insider information, offers a way to succeed in achieving a goal. Just a bird coheres more closely to selected members of its flock than others to achieve a destination, cohering to selected industry leaders offers a possible way of achieving success in reaching certain organizational goals.

Analysts who accept as valid the CAPEM representation of productive efficiency accept the combined building blocks of both DEA and CAS flocking behaviors. Extrapolating from their understanding of combined DEA and CAS flocking behavior building blocks, analyst and organizational decision-makers can identify and decide among policy options. In input-minimization scenarios decision-makers can experiment to determine how closely or how loosely they wish to align with the general membership of the industry, how closely or loosely they wish to cohere with acknowledge industry leaders. Using the CAPEM approach decision-makers can further determine if they wish to maintain some separation from even those whose far productive efficiency is or seems to be closest to their own. A zero separation would give them the option of doing "exactly" what selected others are doing. By establishing certain management measures, metrics and decision processes an organization could choose to do one or any combination of these options. BY using the CAPEM approach and properly tailored CAPEM NetLogo simulation the analyst could provide insights and make informed recommendations.

Appendix C Dynamic Data Envelopment Analysis Models – A Comparison

C.1 Introduction

As the basis for identifying the building blocks of productive efficiency we have chosen to employ a well-respected form of traditional productivity analysis know as Data Envelopment Analysis (DEA) (Koopman, 1951; Farrell, 1957; Charnes, Cooper and Rhodes, 1978). In addition to its respected, and well documented, place among traditional forms of productivity analysis, DEA has the advantage of having been extended to include time in its formulations. This new form of DEA is known naturally, but somewhat inaccurately, as Dynamic DEA (DDEA) (Fare and Primont, 1995). A more truly dynamic version of DEA, known as Dynamic Productive Efficiency Modeling (DPEM) (Vaneman and Triantis 2007), has more recently incorporated System Dynamics (SD) (Sterman, 2000) based representations of continuous time and non-linear relationships, making it more comparable to the building blocks of CAS. Leveraging these previous versions, it is now our intent to further extend DEA into a CAS based form of analysis.

C.2 The Standard DEA Model

Standard DEA is a non-parametric statistical approach to comparing measures of relative productive efficiency in firms, organizations, or systems in which there are multiple inputs and/or multiple outputs, and in which, it is not desirable or possible to aggregate the inputs or outputs into a single measure of relative efficiency (Charnes, Cooper and Rhodes, 1978). Firms, organizations, or systems are treated as single entities known as “decision making units” (DMUs). The objective of DEA is to optimize the productive efficiency of each DMU. The DEA seeks to identify the DMUs from among a family of productive entities with the most extreme productive efficiencies and uses them to benchmark comparisons guide policy and decision-making. This contrasts with regression analysis in which the mathematical application seeks to find measures of central tendency of productive efficiency among DMU. For this purpose productive efficiency is defined as a simple ratio Efficiency = Output/Input (Boussofiane, Dyson and Thanassoulis, 1991).

As with most real systems, DMUs usually have multiple input and multiple output. The previous equation is therefore expanded to the following (Boussofiane, Dyson and Thanassoulis, 1991):

Equation C1.

$$\theta_k = \frac{\sum_{r=1}^{M} u_r \, y_{r0}}{\sum_{i=1}^{N} v_i \, x_{i0}}$$

Subject to:

$$\frac{\sum_{r=1}^{M} u_r y_{rj}}{\sum_{i=1}^{N} v_i x_{ij}} \leq 1 \qquad j = 1,2, \ldots, n$$

$$u_r \; v_i \geq 0; \; r = 1.2, \ldots, m; \; = 1.2, \ldots, m;$$

Where:

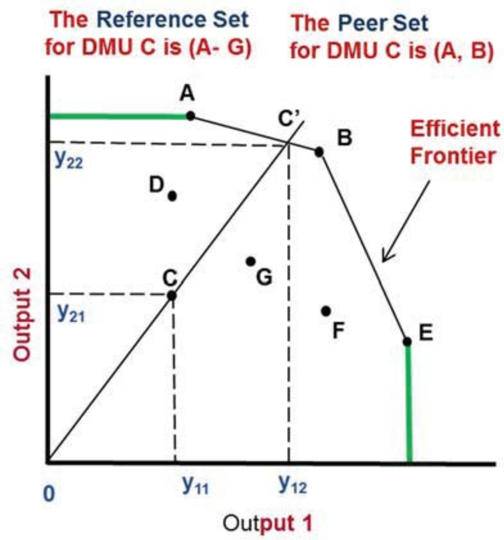
θ_k – the objective function or the measure of productive efficiency
u_r – weight given to output r v_i – weight given to input i
y_{rj} – the amount of output r from the unit k
x_{ij} – the amount of input i from the unit k n
– number of units of input
m – number of units of outputs

This very basic, intuitive definition of efficiency can apply to many forms of "production systems" be they the production of chemicals, electrical power, retail manufacturing, or the production of services such as healthcare and education. Weighted sums of doctors and nurses, for example, produce weighted sums of patients who, having been treated are released from the hospital at various levels of health. Under similar circumstances one hospital may treat and release more patients with a greater level of health than another hospital. The first is considered “more efficient” than the second.

Using the weighted sums of doctors and nurses as inputs and weighted sums of treated patients at various levels of health as outputs we can gain insight into the patterns of productive efficiency and policies that might be available to less efficient hospitals to make improvements and eventually optimize their operations. Since the optimum weights of the inputs and outputs are generally unknown, Equation C-1 was further refined by Charnes, Cooper and Rhodes (1978) into a linear programing model, which is solved for its maximum possible values. Applying these values we determine the maximum possible value of productive efficiency for each DMU. Since each DMU is being given the maximum possible efficiency rating (as opposed to an efficiency rating based on a measure of central tendency), it becomes clear which DMUs are most efficient. All those that are not among the most efficient are judged as being inefficient or at least less efficient than the benchmark formed by the subset of the most efficient DMUs (Charnes, Cooper and Rhodes, 1978).

Figure C-1, below, illustrates the basic building blocks of DEA. The axes of the coordinate scale form the “productive possibility space”. Each axis represents a “factor of production”, which in this case are outputs 1 and 2. Graphical representations are, of course, limited generally to two and three dimensional views even through DEA can readily calculate values for multiple inputs and multiple outputs.

Figure C-1. Graphical Representation of the Major Building Blocks of Standard DEA



Systems and organizations are represented individually as “decision-making units” (DMU), each having a lettered (A-F) positions (*y*, *y*), (*x*, *x*) or (*x*, *y*) in the coordinate space of productive efficiency. Only DMUs that have common characteristics (goals, inputs, outputs) and similar circumstances (common market, common technology, common volumes and scale of operations)” should be compared. This set of DMU is known as the “reference set” (Cooper, Seiford and Tone, 1999).

The piecewise linear curve traversing the productive possibility space is known as the “efficient frontier” (EF). It is defined by connecting with straight lines, the most efficient among the family of DMUs. In this illustration, these are the upper most and right most DMUs in the population of DMU (A, B and E). The efficient frontier indicates, in this case, the line of optimum output efficiency achievable for this family of DMUs. The set of most efficient DMUs are known as the “peer set”.

The efficient frontier is effectively a “benchmark” that can be used by decision-makers to identify “options” and modify “policies”. To become optimally efficient the less efficient DMUs would pursue policies that would bring them ever closer to a point on the efficient frontier between two members of the “peer set”.

In DEA, the analysis of productive efficiency takes on one of two primary approaches, which conform to the two most intuitive ways in which efficiencies can be realized. First, a system or organization can seek to maximize the level of output(s) achieved for a given set of input(s) or alternatively the systems or organization can seek to minimize the input(s) required to achieve a given level of output(s). The linear programing formulation of the “output maximization” approach (Cooper, Seiford and Tone, 1999) is expressed as:

Equation C-2.

$$\mathrm{Max}_z\ \theta$$

$$\sum_{j=1}^{n} z_j x_{ij} \leq x_i^0 , i = 1.2, \dots . m$$

$$\sum_{j=1}^{n} z_j y_{rj} \geq \theta y_r^0 , r = 1.2, \dots . t$$

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

The objective function representing output is being maximized subject to several constraints. These constraints assure that the optimum solution conform to some basic physical/economic laws, known in DEA as the “axioms of production” (Cooper, Seiford and Tone, 1999), which are further explained later in this paper. The first constraint requires two things, first, that there must be some level of input to produce an output and that the weighted sum of the inputs used by the reference set DMUs not exceed the initial amount available. The second constraint requires that the weighted sum of outputs among the reference set be at least as great as the initial outputs of its members times a maximized factor of production. The third constraint requires that the sum of the weights be added to one in which, in terms of physical laws, means that the relationship between outputs and inputs remains the same during production regardless of the scale of the production. This is known in

DEA as a “constant return to scale” (no this is the variable returns to scale representation). Summing to something other than one would mean that the relationship between outputs and inputs would change as the number of units produced changed. The optimization problem would need to be treated as a special “variable returns to scale” case, beyond the scope of this research. Well, the formulation is for variable returns to scale.

The major alternative DEA approach to analysis of productive efficiency is the “input minimization” approach. The linear programming formulation (Cooper, Seiford and Tone, 1999) is expressed as:

Equation C-3.

$$\mathrm{Min}_{Z}\ \theta$$

$$\sum_{j=1}^{n} z_j x_{ij} \leq \theta x_i^0 , i = 1.2, \ldots . m$$

$$\sum_{j=1}^{n} z_j y_{rj} \geq y_r^0 , r = 1.2, \ldots . t$$

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

In this alternative DEA approach the sum of the weighted inputs is required to be less than or equal to the initial level of inputs times a factor of minimized production. The second constraint requires that there not be a reduction in output produced. Third, the variable returns-to-scale constraint remains in place.

CAS approaches to measuring productive efficiency do not use linear programming techniques of analysis but they are useful in identifying and explaining the building blocks of DEA. In place of linear programing CAS employs mathematical formulations that represent the selected CAS metaphor, which in the case of this research is the CAS flocking metaphor.

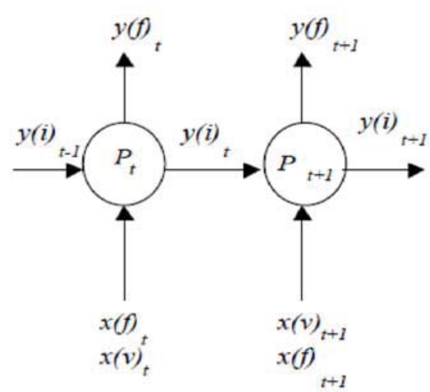
C.3 Dynamic DEA Models

Because standard DEA models are static, single snapshots in time, it is necessary to look at dynamic extensions to determine possible additional building blocks that will assist our research.

C.3.1 The Dynamic DEA Model (DDEA)

Färe and Grosskopf (1996) developed a form of “dynamic” data envelopment analysis (DDEA) by extending the standard DEA model into an infinite sequence of static models or snapshots in time. Figure C-2 below illustrates the concept of DDEA. Each production cycle output set (P) has three types of inputs: fixed (x(f)), variable (x(v)), and inputs that were intermediate outputs to the last production cycle (y(i)). The outputs for each production cycle are the final outputs (y(f)) that represent the products that go to the customer and intermediate outputs that are used as inputs to subsequent production cycles (y(i)).

Figure C-2. The DDEA Basic Structure



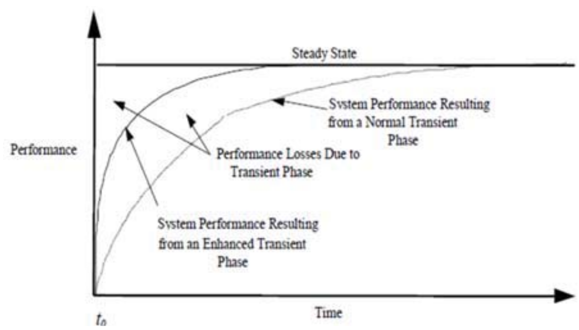
This methodology incorporates time into the standard DEA equations by treating intermediate outputs from a previous production cycle as inputs to the next. Each production cycle is evaluated as with standard DEA as a static linear programing problem. While the approach is called DDEA, no dynamic behaviors are involved.

It does not account for very important dynamic behaviors that occur as a system transitions over time and between these snap shots in time. Each production cycle is assumed to start and remain in a steady state having no change in the level of production of a factor of production within any single increment of time and no change in the rate of change of inputs or outputs between increments of time. No complexity in the pattern of productive efficiency is represented from one snapshot to another. No new building blocks of DEA are provided by DDEA but an understanding of this approach illuminates our understanding of DEA and indicates additional building blocks that will be necessary to address complexity. These additional building blocks are provided in part by the DPEM approach as described below.

C.3.2 Dynamic Productive Efficiency Model

DPEM, as described by Vaneman and Triantis (2007), is a SD-based approach that extends DEA to enable analysis of system behaviors that occur within these increments of time and does not assume steady state throughout. Figure C-3 below illustrates the advantage of doing so (Vaneman and Triantis, 2007).

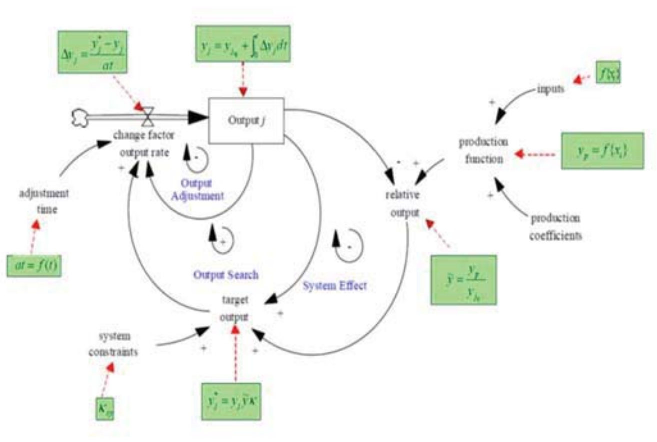
Figure C-3. DPEM System Performance between Steady States



The horizontal line at the top of the illustration represents the efficiency that would be calculated using the standard DEA and DDEA methods. This calculation would overestimate the efficiency of the system in this period of time and would offer no opportunity for improving performance. If, for example, the true normal dynamic transient state for this time period is a form of exponential growth, as indicated by the lower curve, there would in fact be room for improvement. Deeper knowledge of the complexities of the system would lead to meaningful enhancements and increased efficiencies, as indicated by the upper curve.

As shown in Figure C-4 below DPEM incorporates the concepts of SD modeling to account for the internal variability of states of a system throughout periods of time and account for the co-variability of components of a system as they interact over time.

Figure C-4. DPEM Systems Dynamics Model



Each box in the model is a factor of production and each line is a casual relationship between the factors. Each factor of production is represented by an integral, enabling the analyst to represent accumulations or depletions of that factor over time or with respect to other model variables. Each causal relationship is represented by a differential equation enabling the analyst to represent rates of change in the inputs and outputs. Without going further into the intricacies of this specific subject domain and model we see possible solutions that can be used as building blocks of a CAS form of DEA.

C.3.2.1 Adding the Element of Time

In developing DPEM Vaneman and Triantis (2007) examined the various ways in which dynamic systems were represented mathematically. Among the major theoretical constructs only the dynamical, causal, and closed systems construct allowed for examination of systems in a non-steady state condition during the period of transition and enable the analyst to influence the system behavior in the transition period. It is the dynamical, causal, closed systems construct then that we will use as a DEA building block for representing and analyzing system productive efficiency and for making comparisons with CAS flocking behaviors. In both the CAS flocking metaphor and dynamical, causal, closed systems, behaviors are modified by introducing inputs via internal feedback mechanisms. DPEM extension of DEA productive efficiency in these systems is expressed as:

Where the final element of the output function y_j $(t_d\text{-}t_0)$ is the jth output resulting from behaviors during the interval $[t_0, t_d]$ or the output resulting from behaviors that began at the beginning of the time increment to the current point of measurement. By including the output resulting from behaviors up to the current point of measurement the DPEM approach to productive efficiency incorporates results from past actions and enables them to influence future actions. In SD this is done via an explicit feedback mechanism. Vaneman and Triantis (2007) also confirmed that including the time increment into the output variable was valid for each of the axiom of production. It is this concept of including changes within the time increment and the output variable and incorporating the results from past or even external actions in the measure of productive efficiency that makes possible to understand the extension of DEA into CAS flocking behaviors with respect to time. The CAS flocking metaphor does not employ explicit feedback mechanisms for these time variables. However, inherent in "flocking" alignment, cohesion and separation is time dependent agent communication that likewise incorporates the effects of changes in previous increments of time to influence current behaviors.

C.3.2.2 Equilibrium and Stability

The DPEM extension also enables the analyst to understand the non-steady state nature of the system during transition. For definitions of these concepts Vaneman and Triantis (2007) again employed the SD paradigm. The same definitions can be employed to gain a deeper understanding of CAS flocking behaviors. In the SD paradigm systems are categorized as being in equilibrium or in disequilibrium, stable or unstable. Equilibrium can be further categorized as either static or dynamic. Static equilibrium is defined as the condition $y_{jt} = (t - t_0;\, x_{it0};\, x_{itd};\, x_{j(td-t0)})$ that exists when there is no flow or no change in behavior within the system. Two conditions must be satisfied for a system to be in static equilibrium: (1) all first order derivatives of inputs and outputs, dx_i , dy_{jt} , are zero at the time considered and (2) all higher order derivatives are also zero. A system in which only condition (1) is satisfied is said to be momentarily at rest (Frisch, 1935).

A system in dynamic equilibrium is a system where there is a constant flow or a constant rate of change going through the system. Viewing the system from a macro level, dynamic equilibrium gives the appearance that nothing within the system changes over time. A closer look reveals that there is a constant flow of inputs into the system, and a constant flow of outputs from the system (Sterman, 2000). All derivatives will have non-zero values for dynamic equilibrium. A system that does not meet the criteria for either static or dynamic equilibrium is said to be in a state of disequilibrium (Frisch, 1935). An example of a system in disequilibrium is a manufacturing plant where there is a constant influx of orders, and the number of orders exceeds the plant capacity. In this case the queue of orders will continue to grow, thus creating a state of disequilibrium.

System stability refers to how a system that was previously in equilibrium behaves when a disturbance is introduced. Consider a small disturbance introduced to the system at time td. If the system returns to its original (or closely related) state of equilibrium after being disturbed, the system is considered stable (Frisch, 1935), (Sterman, 2000). If the small disturbance forces the system further away from equilibrium with the passage of time, the system is said to be in unstable equilibrium.

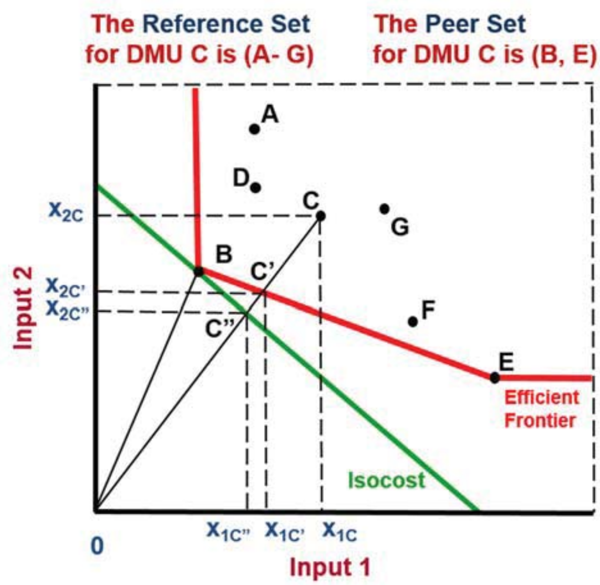
These same definitions are useful in understanding the relationship between the CAS flocking metaphor and DEA/DPEM approach to productive efficiency.

C.3.2.3 Technical and Allocative Efficiency Measurement

Färe and Lovell (1978) define the production function as a scalar output that specifies the maximum output obtainable from an input vector. Thus the production function describes a technical relationship between the inputs to the production process and the outputs from the production process. Technical efficiency (TE) reflects the firm's physical ability to produce the maximum output for a given input. If this condition is met, the unit is said to be operating on its production frontier. A technically inefficient unit will be operating below the production frontier, thus not optimally using its inputs to produce outputs (Farrell, 1957), (Coelli, Rao and Battese, 1998).

As TE characterizes the physical efficiency of transforming inputs into outputs, allocative efficiency characterizes the economic or price efficiency associated with transforming inputs into outputs (Farrell, 1957). Figure C-5, below dichotomizes productive efficiency into its two sub-components: technical and allocative. This figure represents points A and B during a single time period (static sense), with two outputs y_1 and output y_2, and one input x by comparing them to the "unit isoquant" (line xx') and "isocost" (line cc') lines.

Figure C-5. Building Blocks of Productive Efficiency



This approach allows for the analysis of productive efficiency by comparing the measured values with respect to the isoquant and isocost lines. If a DMU lies on the isoquant, it is deemed technically efficient. If is lies on the isocost line, it is deemed allocatively efficient (AE). And if it lies at the intersection of the isoquant and isocost lines, the DMU is deemed both technically and allocatively efficient. The area below the isoquant is the inefficient region, and the area above the isoquant is the infeasible region. I would suggest that you use the input space to convey these notions because in output space we with have iso-revenue or iso-profit lines.

With the assistance of Figures C-5 and C-6, the mathematical relationships for allocative efficiency, technical efficiency, and overall productive efficiency can be shown. The following definitions are provided by Farrell (1957):

TE is mathematically defined as: TE = 0C'/0C

AE is defined as: AE = 0C"/0C'

Overall productive efficiency (OPE) is defined as:

$$OPE = (TE)\ (AE) = (0C''/0C')\ (0C'/0C)$$

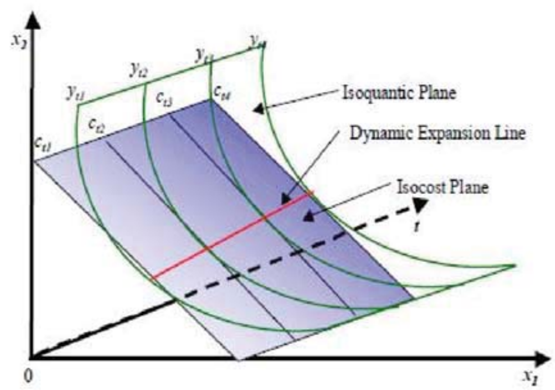
In Figure C-5, above, point B lies at the intersection of the isoquant and isocost lines, thus is deemed both technically and allocatively efficient with respect to point A. Point A' is initially located to the southwest of the isoquant, thus is deemed technically inefficient. By incorporating process improvements, a weighting factor less than 1 is applied to point A, the outputs are produced more efficiently such that the DMU is able to produce the greater amounts of outputs with the same input. This action plots point A' on the isoquant. Incorporating process improvements based on cost, a different weighting factor, also less than 1 is applied, and point A is adjusted further. This action now places point A' on the isocost line. Subsequently the system can now be deemed to technical efficient or allocative efficient but not both. For point A to be both technically and allocatively efficient, the processes must be changed to resemble the process used at point B.

A few caveats to Figure C-5 are necessary. First, the assumption is being made that the production function is being operated under constant returns to scale, meaning that regardless of the number of units of input the outputs remain in the same proportion. Second, the production frontier is known. In general production frontier is not known and must be estimated (Coelli, Rao and Battese, 1998).

The dynamic efficiency plane, Figure C-6, expands the discussion further. This graph portrays two input axes x_1 and x_2, and a time axis t. In this graph the isoquants are increasing to the northeast. In a continuous time problem the level of output y is represented by an isoquantic plane. Likewise, the isocost lines are also represented in continuous time, and are depicted as the isocost plane. In a two-dimensional (or static) representation, overall productive efficiency is achieved at the point of tangency between the isoquants and isocost lines (as depicted by point b in Figure

C-6. In a continuous time environment overall productive efficiency is achieved along a line where the isoquant and isocost planes are tangential. This line is known as the dynamic expansion line 3. The dynamic expansion line represents the most efficient (overall productive efficiency) path to traverse during a transient period $[t_0,t]$.

Figure C-6. The Dynamic Efficiency Plane



Appendix D Agent-Oriented Formulations for the Performance Measurements Interrelationship Problem

D.1 Abstract

This paper was written originally in preparation for a DEA conference. Csaba Egyhazy, Associate Professor, Computer Science, Virginia Tech was the primary author. The ideas expressed here were initially developed by Francis L. Dougherty, Senior Principal Information Systems Engineer, The MITRE Corporation. The collaboration was begun and facilitated by Dr. Kostas Triantis, Professor, Industrial and Systems Engineering, Virginia Tech.

D.2 Introduction

"What Gets Measured Gets Done" (Williamson, 2006, p.1). This axiom often accredited to Peter Drucker as well as others is often quoted but seldom achieved. Why? Because measurement requires a degree of rigor and discipline that is beyond the day-to-day activities of most mangers. It is one thing to articulate goals and objectives in a narrative and display them in a presentation to the board of directors. It is another to define measures, collect data, analyze the data, present findings and make recommends to that same board. The later requires mastery of the Performance Measurements Interrelationship problem.

The Performance Measurements Interrelationship problem is about identifying the key elements of an enterprise that lead to desired outcomes, defining and measuring cause and effect interrelationships among these elements, and then using these measurements to gain insights and draw conclusions. Reasoning about performance measurements, and their interrelationship requires a notation, and rigor that is not normally exercised in day-to-day management. It is our purpose here to investigate the use of agent-oriented formulations to capture the existence/nonexistence of cause and effect among a pair of performance measures, and the rules (i.e., semantics) necessary to reason about their interrelationships.

In recent years agent technology has been successfully applied to many different domains. Because this technology features the use of artificial intelligence to coordinate data collection, and support decision-making, it provides a powerful basis for proactive applications for organizations seeking to improve performance. Identifying and utilizing the large number of possible cause and effect relationships among performance measures at various levels of aggregation require tasks well suited for software agents. Agents are self-contained programs capable of controlling their own decision-making and acting, based on its perception of its environment, in pursuit of one or more objectives (Jennings, 1996; Nwana, 1996). Every agent exhibits the characteristics of autonomy, reactivity, proactiveness, and the ability of learning and interacting with other agents in a manner similar to the way humans do.

The de facto model for an agent is the Belief, Desire, Intent (BDI) Model (Padgham, 2004), where an agent has associated with it beliefs, desires and intentions. Beliefs correspond to the information that the agent has about the world. In practical terms it can be viewed as the state of the world and it can be represented as simple variables or data structures or complex systems such as knowledge bases. Desires represent the things that the agents would wish to do, and intentions represent the desires that the agent is committed to achieve.

In Section D-3 below we summarize the building blocks used in modeling the Performance Measurements Interrelationship problem. In Section D-4, we provide a number of agent-oriented formulations for key concepts in Performance Measurements Interrelationship, and in Section D-5, we provide conclusions, and directions for future work

D.3 Background

In framing the Performance Measurements Interrelationship problem, we used the concepts contained in the United States Government's Federal Enterprise Architecture Performance Reference Model (OMB, 2006), which is itself based on the W.K Kellogg Program Logic Model (Kellogg, 2004).

D.3.1 The W.K. Kellogg Foundation Logic Model

W.K. Kellogg Foundation (Kellogg, 2004, p. 1) defines their program logic model as "a systematic and visual way to picture of how an organization does its work." The program logic model "links outcomes (both short- and long-term) with program activities/processes and the theoretical assumptions/principles of the program." Rather than using the more common workflow models, which can become very involved and complex, the Kellogg model uses a simple input-output model to describe how organizations do their job. Inputs are the people, technology and other resources an organization has to accomplish their mission. Organizational processes such as fund-raising, collaboration, and decision-making transform the resources into outputs, which lead to achievement of the organization's desired outcome or result, and eventual overall strategic impact. The model has been used successfully in many areas of business over a number of years.

D.3.2 The Federal Enterprise Architecture Performance Reference Model (FEA PRM)

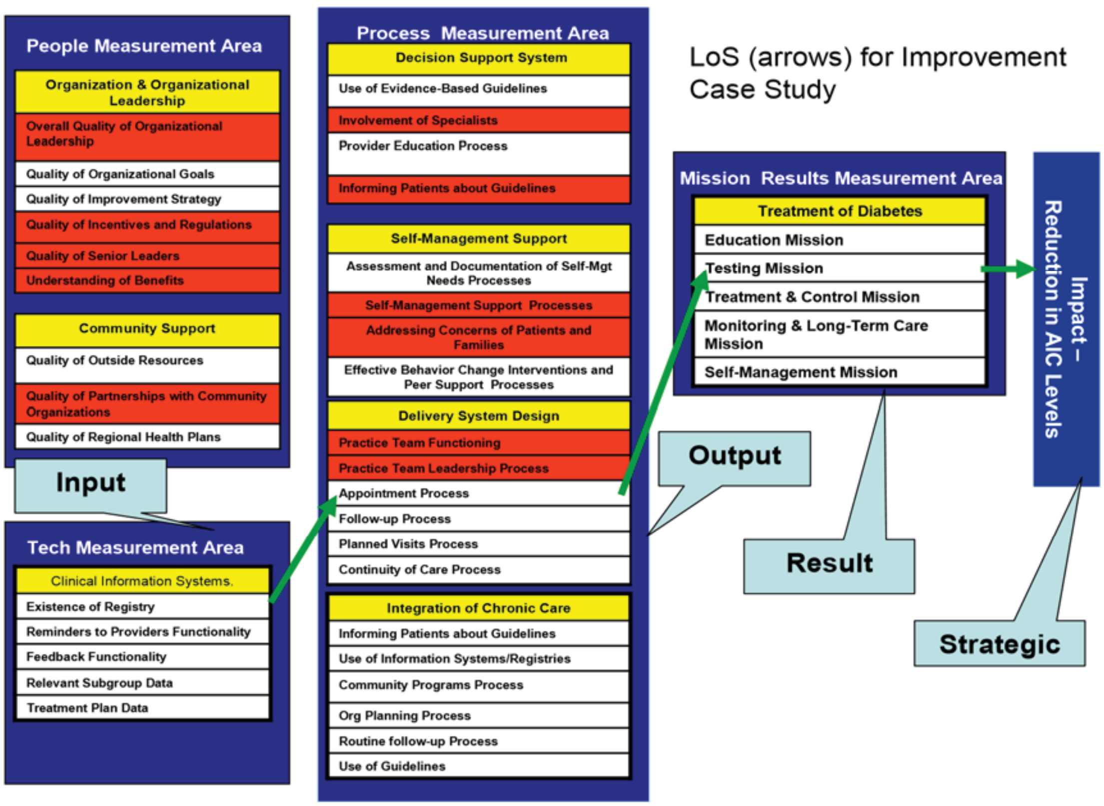
Together with the Business, Service Component, Data, and Technology Reference Models the FEA PRM is used by the United States (US) Government to describe and study its own organization, functions and interrelationships. The FEA PRM provides the US Government with an agreed upon lexicon, structure and logic that enables its many unique and widely varied agencies to communicate about performance and collaborate to achieve results.

Using the concepts of the Kellogg Program Logic Model, the FEA PRM is organized into six measurement areas, one each for People, Technology, Fixed Assets, Processes & Activities, Mission Results, Customer Results, and Strategic Impact. Measurement areas are decomposed into measurement categories, and further decomposed into measurement groupings of individual measurement indicators. The six measurement areas form a pyramid with 4 layers. The bottom layer, the "Input Layer" includes the People, Technology and Fixed Assets that serve as resources (inputs) to the next layer, the "Output Layer". The Output Layer contains only the Process & Activities measurement areas, but it contains all processes and activities employed by all government agencies to transform people, technology and fixed assets into government services (outputs). Outputs achieve certain Mission or Customer Results which are the measurement areas contained in the 3rd or "Outcome/Results Layer" of the pyramid. The 4th layer and point of the pyramid is formed by a single measurement area, which the FEA PRM calls "Strategic Outcome." Strategic Outcome is synonymous with "impact."

D.3.3 Lines of Sight

Integral to the FEA PRM is the concept of a Line of Sight (LoS) (OMB, 2006). A LoS is a thread linking measures in each of the 4 Layers of the FEA PRM. The arrows in Figure D-1 below show a LoS starting with a measure from within the Technology measurement area, which links to a measure within the Process measurement area, which links to a measure in the Mission Results measurement area, which finally links to a measure in the Impact measurement area. The LoS asserts that there is a measurable cause and effect relationship between inserting a technology (input, i.e., use of a registry) and changes in process (output, i.e., the appointment process); that there is then a measurable cause and effect relationship between the change in the process and a change in the Mission Results, and ultimately a cause and effect relationship between a change in Mission Results and Impact.

Figure D-1. Sample PRM and LoS for Adopted Case Study



The LoS gives us the ability, once validated, to measure and demonstrate the value of making changes in people, technology or processes. There are a large, sometimes infinite, number of possible LoS, which can be reduced by a number of valid techniques, to the set of threads of most interest to the decision-maker. Once reduced to a reasonable set, the LoS can be investigated collectively, in combination, or individually. It is the investigation of the options raised by these sets of LoS that provides the insights needed for understanding, communication and making decisions. It is to this investigation of options we seek to apply agent-based modeling.

D.3.4 Adopted Case Study

As a means of illustrating concepts and limiting scope, we have selected a real world performance measurement case study available through the Institute for Health Improvement public website (IHI, 2003). In this case study, entitled “Tarheels Take on Diabetes,” the North Caroline State Diabetes Collaborative seeks to find ways to best use grant funds to improve care to underserved rural diabetes patients. The case study provides a model for care (organizational components and processes), measures of performance, and the data it collected in the first phase of the study. The case study ends with the Collaborative pondering ways to best use funds in the Phase 2 of its efforts.

For this paper we have drawn from the public website the information needed to populate and use the FEA PRM. Figure D-1 illustrates the adaptation of information from the case study to produce a sample FEA PRM. In this figure, we turned the FEA PRM on its side with the Input Layer starting on the left. The measurement areas are the same as in the FEA PRM except that the Fixed Asset and Customer Results measurement area were not needed in this case study. The measurement areas are decomposed into categories and groupings, just as in the FEA PRM, but the identity of these categories and groupings of measures is unique to the this case study. The measurement indicators for the individual groupings are no shown here, but are illustrated for two sample groupings in Section 3.4.

D.4 Agent-Oriented Formulations

One way of testing the suitability of a particular technology to a specific problem is to determine how easy it is to formulate the problem using a notation and expressions akin to that technology. In the case of agent technology, this reduces to determining how easily we can express the models and concepts introduced in Section 2 by way of a symbolic notation, and logic statements.

D.4.1 Formulating the FEA PRM

We begin by providing shorthand to denote the four levels of the FEA PRM, namely I for Input, O for Output, R for Result, and S for Strategic. As seen in Figure D-1, level I has 3 measurement areas: People, Tech, and Fixed Assets. We denote each measurement area by ah. In this case, h = 1, …, 3 maps to People, Techology, or Fixed Assets. Within each ah there is any number of measurement categories, which we denote by c_j. In this case study, the People Area has 2 categories (j = 1, 2), the Organization and the Community. Consequently, if we chose to denote the People measurement area by a1 then the Input (People measurement area - Community measurement category) is denoted by $I(a_1,c_2)$. The Technology measurement area has only 1 category, the Clinical Information Systems, while the Fixed Asset Area was not used in the case study.

From Figure D-1, we see that the next level of granularity corresponds to measurement groups. Within each measurement category there are any numbers of measurement groups, which we denote by g_k. In this case study, Clinical Information Systems category has 5 measurement groups, thus k = 1,..5. Consequently, if we chose to denote the Tech measurement area by a_2, the Clinical Information Systems by c_1, and the Existence of Registry by g1 then the Input (Tech measurement area - Clinical Information Systems measurement category - Existence of Registry measurement group) is denoted by $I(a_2,c_1,g_1)$.

The finest level of granularity, not shown in Figure D-1, is the measurement indicators. Within each measurement group there are a number of measurement indicators, which we denote by i_m. In our adopted case study, each measurement group has 4 measurement indicators, thus m = 1,..4. Consequently, if we again chose to denote the Tech measurement area by a_2 , the Clinical Information Systems by c_1 , the Existence of Registry by g1 and a measurement indicator, say m = 2, then the Input (Tech measurement area - Clinical Information Systems measurement category - Existence of Registry measurement group – measurement indicator 2) is denoted by $I(a_2,c_1,g_1,i_2)$.

In general, any Input element is denoted by:

Equation D-1. $I(a_h, c_j, g_k, i_m)$

Level Output (O) in this case study has only one measurement area, namely the Process measurement area. It has within it 4 categories which are Decision Support Processes, Self-Management Processes, Delivery System Design, and Integrated Care Processes. Each category in turn has a number of measurement groups, and each measurement group has 4 measurement indicators. Following the same ideas for the above notation, if we chose to represent Delivery System Design by c4, and Appointment Process measurement group by g_1 , and a measurement indicator, say m = 2, we denote the Output (Process measurement area – Delivery System Design measurement category – Appointment Process measurement group – measurement indicator 2) by $O(a_1,c_4,g_1,i_2)$.

In general, any Output element is denoted by:

Equation D-2. $O(a_h, c_j, g_k, i_m)$

Level Result (R) has one measurement area, which is the Mission Results measurement area, and one measurement category, namely Treatment of Diabetes. As seen from Figure D-1, the Treatment of Diabetes measurement category has 5 measurement groups, and each measurement group has 4 measurement indicators (not shown). In a similar fashion as above, if we chose to represent Testing Mission measurement group by g_2 , and a measurement indicator, say m = 2, we can denote the Result (Mission Results measurement area – Treatment of Diabetes measurement category – Testing Mission measurement group – measurement indicator 2) as follows: $R(a_1,c_1,g_2,i_2)$.

In general, any Result element is denoted by:

Equation D-3. $R(a_h, c_j, g_k, i_m)$

The final level, Strategic (S), has no measurement area, category, or group, only measurement indicators. Therefore, if we chose a measurement indicator, say m = 3, we denote the that Strategic level by $S(i_3)$.

In general, any Strategic element is denoted by:

Equation D-4. $S(i_m)$

D.4.2 Cause and Effect Relationships Among Performance Measures

Knowing the cause and effect relationships among performance measures is a necessary condition for defining the LoS, and for our ability to reason about performance measures. One question we need to answer is at what level of granularity are we to define the existence of a cause and effect relationship among two adjacent nodes in a graph? After reviewing the performance measures reported in the adopted case study, we concluded that a reasonable choice is to consider cause and effect relationship at the measurement group (g) granularity level for I ,O, and R, and at the measurement indicator (i) granularity level for S. We can now represent the existence/nonexistence of a cause and effect relationship between any I node and O node as $\{I(a_h, c_j, g_k), O(a_h, c_j, g_k)\}$, between any O node and R node as $\{O(a_h, c_j, g_k), R(a_h, c_j, g_k)\}$ between any R node and S node as $\{R(a_h, c_j, g_k), S_i\}$. To denote the existence or non-existence of a cause and effect relationship between any two nodes, we append a 1 or 0 respectively to their node pair. For example, using Figure D-1, if there is a relationship between measurement groups “Existence of Registry” and “Appointment Process” we denote it as:

Equation D-5. $\{I(a_2, c_1, g_1), O(a_1, c_3, g_3) , 1\}$

If there is no cause and effect relationship between, say R and S, we use

Equation D-6. $\{R(a_1, c_1, g_2), S_1, 0\}$

Given this notation, we next formulate the concept of a LoS.

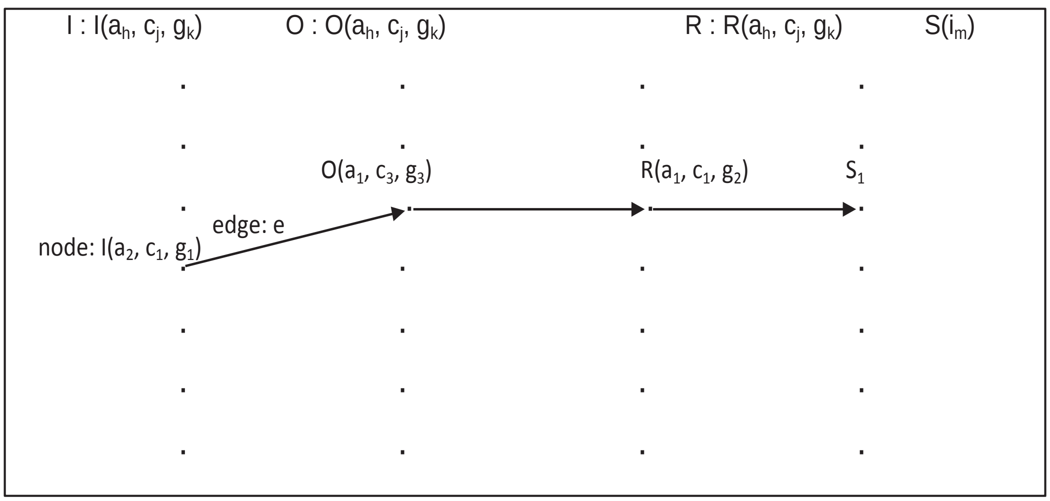
D.4.3 Formulating the Concept of LoS

As shown in Figure D-1, the LoS is a path comprised of three arrows, the first one connects “Existence of Registry” to “Appointment Process” to ”Testing Mission” to an unspecified S measurement indicator (assume i=1). Using the notation developed above, we can represent this particular LoS (i.e., $(LoS)_1$) is as follows:

Equation D-7. $\{I(a_2, c_1, g_1), O(a_1, c_3, g_3), 1\}$, $\{O(a_1, c_3, g_3), R(a_1, c_1, g_2), 1\}$, $\{R(a_1, c_1, g_2), S_1, 1\}$

To generalize the above expression, we view Figure D-1 as a graph, as see in Figure D-2, where measurements are nodes and arrows are edges (e) that connect nodes. LoS is now seen as a directed path with 4 nodes (I, O, R, and S, in that order) and 3 edges (I-O, O-R, and R-S, in that order).

Figure D-2. Directed Graph for Lines of Sight



The first edge must go from an I node to an O node, which is to say that I nodes and O nodes are consecutive and that an I node precedes an O node. A similar view holds for the second and third edges. Next, we provide some logical statements to express the semantics behind the concept of LoS, namely that

Equation D-9. $\forall\ (e, I(a_h, c_j, g_k), O(a_h, c_j, g_k))$: source $(e, I(a_h, c_j, g_k)) \wedge$ target $(e, O(a_h, c_j, g_k)) \rightarrow$ adjacent $(I(a_h, c_j, g_k), O(a_h, c_j, g_k))$

Equation D-10. $\forall\ (I(a_h, c_j, g_k), O(a_h, c_j, g_k))$: adjacent $(I(a_h, c_j, g_k), O(a_h, c_j, g_k)) \rightarrow$ adjacent $(O(a_h, c_j, g_k), I(a_h, c_j, g_k))$

Equations D-9 and D-10 state that nodes I and O are adjacent.

Equation D-11. $\forall$ (e, I(a_h, c_j, g_k), O(a_h, c_j, g_k)): source (e, I(a_h, c_j, g_k)) $\wedge$ target (e, O(a_h, c_j, g_k)) $\rightarrow$ parent (I(a_h, c_j, g_k), O(a_h, c_j, g_k))

Equation D-12. parent (I(a_h, c_j, g_k), O(a_h, c_j, g_k)) $\rightarrow$ path (I(a_h, c_j, g_k), O(a_h, c_j, g_k))

Equations D-11 and D-12 state that if I node is parent of O node, then there is a direct path from I to O.

Equation D-13. parent (I(a_h, c_j, g_k), O(a_h, c_j, g_k)) $\wedge$ path (O(a_h, c_j, g_k), R(a_h, c_j, g_k)) $\rightarrow$ path (I(a_h, c_j, g_k), R(a_h, c_j, g_k))

Equation 9 defines a path of directed edges from I to R.

Equation D-14. $\forall$ (I(a_h, c_j, g_k), O(a_h, c_j, g_k), R(a_h, c_j, g_k), Si_m): path (I(a_h, c_j, g_k), R(a_h, c_j, g_k)) $\wedge$parent (R(a_h, c_j, g_k), Si_m) $\rightarrow$ path (I(a_h, c_j, g_k), Si_m)

Equation D-13 defines an LoS, and Equation D-14 denotes any one LoS, i.e. $(LoS)_n$ where n is an integer specifying a particular LoS.

Equation D-15. {I(a_h, c_j, g_k), O(a_h, c_j, g_k), 1} $\wedge$ {O(a_h, c_j, g_k), R(a_h, c_j, g_k), 1} $\wedge$ {R(a_h, c_j, g_k), Si_m, 1}

D.4.4 Reasoning About Performance Measurements

The syntax and semantics for LoS given above, and the conceptualization provided by the Constraint Satisfaction Problem (CSP) (Neagu, 2005), gives us a starting point for the formulation of a number of applications involving performance measurements, their values, and interrelationships. Next, we propose an expression for a single performance value obtained from measurement indicators i, the finest level of granularity of measurement defined in this paper. Using sample measurement indicators, given on a scale of 0-11, defined in our adopted case study for "Existence of Registry" or I (a_2, c_1, g_1) we have:

…is not available. 0, 1, 2

…includes name, diagnosis, contact information and date of last contact either on paper or in a computer database. 3, 4, 5

…allows queries to sort sub-populations by clinical priorities. 6, 7, 8 …is tied to guidelines that provide prompts and reminders about needed services. 9, 10, 11

where the last three numbers after each of the four i represent the possible values that I can attain. Assume the given i is "… includes name, diagnosis, contact information and date of last contact either on paper or in a computer database" and its value is 4. We denote this as follows:

$V(I(a_2, c_1, g_1, i_2)) = 4$

Similarly, given for "Appointment Process" or $O(a_1, c_3, g_3)$ we have:

…can be used to schedule acute care visits, follow-up, preventive visits. 0 1 2

…ensures scheduled follow-up with chronically ill patients. 3 4 5 …are flexible and can accommodate innovations such as customized visit length or group visits. 6 7 8

…includes organization of care that facilitates the patient seeing multiple providers in a single visit. 9 10 11

Assume the given i is "…are flexible and can accommodate innovations such as customized visit length or group visits" and its value is 8. We denote it as follows:

$V(O(a_1, c_3, g_3, i_3)) = 8$

Further, assume that for "Testing Mission" or $R(a_1, c_1, g_2)$ we have: $V(R(a_1, c_1, g_2, i_1))=3$, and $V(Si_2)=5$, the performance value of that LoS is obtained as follows:

$V(LoS_1) = V(I(a_2, c_1, g_1, i_2)) + V(O(a_1, c_3, g_3, i_3)) + V(R(a_1, c_1, g_2, i_1)) + V(Si_2) = 4 + 8 + 3 + 5 = 20$ In general:

Equation D-16. $V(LoS_n) = V(I(a_h, c_j, g_k, i_m)) + V(O(a_h, c_j, g_k, i_m)) + V(R(a_h, c_j, g_k, i_m)) + V(Si_m)$

Next, we extend the above to provide an expression for a performance value for all the quantifiable LoS for the "Testing Mission", i.e. $R(a_h, c_j, g_2)$.

$V(R(a_h, c_j, g_2))$: $V(\sum_{n=1}^{n}(LoS)_n)$ where every $(LoS)_n$ has to be of the form:

Equation D-17. $\{I(a_h, c_j, g_k, i_m), O(a_h, c_j, g_k, i_m), 1\} \wedge \{O(a_h,c_j, g_k, i_m), R(a_h, c_j, g_2, i_m), 1\} \wedge \{R(a_h, c_j, g_2, i_m), Si_m, 1\}$

Expression D-15 can be abstracted to compute a single performance value for the enterprise (E), as the sum of the performance values across all missions.

V(E): $V(\sum_{n=1}^{n}(LoS)_n)$ where every $(LoS)_n$ has to be of the following form:

Equation D-18. $\{I(a_h, c_j, g_k, i_m), O(a_h, c_j, g_k, i_m), 1\} \wedge \{O(a_h, c_j, g_k, i_m), R(a_h, c_j, g_k, i_m), 1\} \wedge \{R(a_h, c_j, g_k, i_m), Si_m, 1\}$

An immediate benefit of the above formulation is that we can now define performance improvement (Imp) as a function of performance measurement values. For example, if the past value of the enterprise, as defined by Equation D-17), is Vp (E), and the current value of the enterprise is Vc (E), then:

Equation D-19. $V(ImpE) = V_c (E) - V_p (E)$ similarly, the

improvement value for a mission is given by:

Equation D-20. $V(ImpR) = V_c (R) - V_p (R)$, where $V_c (R)$ and $V_p (R)$ are detailed in equation D-15 at the LoS is:

Equation D-21. $V(Imp\ LoS) = V_c (LoS) - V_p (LoS)$, where $V_c (LoS)$ and $V_p (LoS)$ are detailed in equation 14

The reasoning agent is now in a position to, for instance, identify sets of improvements that can be attained given additional levels of, for example, funding (i.e., a constraint). Examples of other higher-order constraint are people, time, and physical assets. The solution to this Boolean Constraint Satisfaction Problem (BCSP) (Neagu, 2005) would in this case represent multiple sets of LoS, each satisfying the funding constraint, and representing different improvement values, computed using equations D-19, 20, 21.

Similarly, given a certain level of future funding for an ongoing mission, we can determine which LoS should be funded to maximize an improvement value. Examples of other higher-order constraint are people, time, and physical assets. In summary, reasoning over performance measurement interrelationships expressed as a BCSP would be directly implemented by agent-oriented software by using well known BCSP algorithms such as those found in (Russell, 2003).

D.5 Conclusions and Future Work

We found the Kellogg Program Logic Model/FEA PRM to be a simple yet robust approach to both understanding the "way the organization works" and to begin an analysis of ways to improve its impact. We found that the information available on the IHI website, while not exhaustive, was quite sufficient for this early stage our research. As we delve deeper into the study we will likely need to collaborate directly with either the IHI or the Diabetes Collaborative itself.

In conceptualizing the Performance Measurement Interrelationship problem, we found the Prometheus methodology (Padgham, 2004) for agent-oriented modeling very helpful. It allowed us to proceed from problem statement to agent-oriented formulations in a disciplined and organized way. In the future, we will identify possible roles for agents, such as specific measurement collection and monitoring, reasoning, and decision making, and analyzing their interactions. Roles normally consist of four attributes: responsibilities, permissions, activities, and protocols. We also plan to model organizational units responsible for managing performance measurements, so that the software support system's behavior closely resembles the interaction between the data collection mechanisms and its use in decision making.

In modeling PRM and LoS, we found that they provide the necessary foundation for agent-oriented facts, rules, percepts, and that the directed graph approach represented sufficiently all necessary concepts and relationships.

We found that a reasoning agent, supported by a knowledgebase containing data about cause and effect relationships, improvement values, and constraints, was a simple and effective design strategy for addressing the Performance Measurements Interrelationship problem. Also, that it is very well suited for identifying and quantifying the often large number of possible improvement strategies available (i.e., set of possible LoS).

In building such a knowledge base, we envision using a process and appropriate technologies (software tool) such as the Pearson Corporations MyManagement (Speckler, 2013) to capture, manage and use an evolving knowledge base to make the best most informed decisions possible. The use of the logic model, lines of sight and the deirct graph notation will facilitate determination and presentation of the most useful options. From these options recommendations tailored to the needs of the manager/decision-maker will be derived and employed to take action. Using various manager friendly questions and short fill-in-the-blank kinds of answers the tool would elicit from the managers their needs and sufficient information to guide the tailoring/refinement of appropriate agents. Using agents capable of performing various proven analytic techniques and methods the tool would then generate options and recommendations. By responding again to short prompts mangers would accept, reject or prioritize the options and/or approve certain recommendations. Additionally, when desired, managers would be able to exam the data, methods and reasoning that led to the options and recommendations. As a result managers could count on My Management to provide easily understood answers to very complex questions and, as desired, have the ability to burrow more deeply to gain insight and lessons learned.

As far as the authors are aware no such tool currently exists. Such a tool would finally enable managers to be actively involved in rigorous disciplined performance measurement without being overcome by the details. They would therefore be far more likely to overcome hurdles to achieving the axiom accredited to Peter Drucker quoted at the beginning of this paper, that is, “What Gets Measured Gets Done” (Williamson, 2006). Being more easily measured, projects would therefore be much better managed.

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