# CHAPTER 5

# SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

In this age of global competition, organizations must continually adopt and exploit new technology (systems and processes) to remain competitive. Unfortunately, adopting new technology often brings unexpected consequences to an organization that is expecting long-range competitive gains. Incomplete mental models or the lack of data with sufficient detail often plague implementation decisions. Thus, evaluating the performance of dynamic systems is becoming increasingly important for efficiency studies. To date, many of the methods used to evaluate the productive efficiency of dynamic systems has been by comparing system inputs to system outputs. However, merely searching for patterns of efficiency is not enough to improve system performance in the future. The purpose of this research is to introduce a methodological approach that combines two time-tested methodologies - system dynamics (SD) modeling and the measurement of productive efficiency – to evaluate productive efficiency in a complex and dynamic environment.

This chapter is a summary of the lessons that were learned, and the conclusions that were drawn, as a result of this research. Section 5.1 revisits the research motivation and discusses the philosophical departure that this study makes with the body of literature. Section 5.2 re-addresses the three hypotheses of this research, and their outcomes. Section 5.3 suggests points of demarcation where new research initiatives can be pursued.

## 5.1 Closing the Loop on the Research Motivation

The impetus of this research was to find a way to evaluate system performance in a complex and dynamic environment. The efficiency literature has primarily been interested in system performance measurement rather than causation, because it was thought that: (i) uncovering the pattern of efficient and inefficient practices should be paramount; and (ii) that the comparative advantage is with performance measurement and not determining the causal factors associated with system performance (Färe *et. al*., 1994).

Heretofore, the productive efficiency methodologies have used system measurement techniques to determine best practices and to establish new performance goals. The fundamental, but often unwritten, assumption in the literature is that the systems being evaluated are in a steady state of operations. Thus comparing measurements from various decision making units to find the best practices, and to establish improvement goals is a credible approach as it is assumed that the last period and the next period are very much like the current period. This methodology is well suited for systems that can be defined as dynamic and historical. While this approach is well suited for the steady state environment, it cannot address productive efficiency in an environment where the system is transitioning from one state to another.

The approach taken by this research does not refute the validity of the methodology expressed in the literature, but offers a philosophically different perspective to address problems associated a different type of system - the dynamic, causal and closed system. The fundamental premise of this research is that the true advantage in understanding productive efficiency in a dynamical, causal and closed system is through the understanding of systemic causes of inefficiencies. This can only be achieved with a sound understanding of how system structures, decisions, and policies are interrelated, and how they interact to form the behavior of the system.

Measurement is important in a dynamic and causal environment to establish a baseline from which a starting point can be gleaned. These initial measures of performance must be inserted into the system, and projected forward through causal relationships to find the system's future behavior. It is only through this simulated foresightedness that system goals can projected as to influence future productive performance during transitional periods.

## 5.2 Conclusions about the Hypothesis

### 5.2.1 Hypothesis 1

*The theory of productive efficiency can be extended into the dynamical realm by incorporating certain concepts within a SD framework.*

This research has proven that the theory of productive efficiency can by extended into a dynamic realm by incorporating certain concepts with a SD framework.

One of the fundamental beliefs at the outset of this research was that DEA could be incorporated directly into a SD framework analogous to the way that the concept was extended into the time domain to create DDEA (Färe and Grosskopf, 1996). This approach appeared to be a natural extension to the DDEA frameworks as it would add the non-linear aspect that was noticeably missing from the DDEA framework. However, after months of attempting to link the two frameworks, I concluded that my original belief was not possible due to the basic structural and philosophical differences.

DDEA, as defined by Färe and Grosskopf (1996), employs their network technology model with a time step introduced. This model allows for inputs to be applied across all time periods, or distinctly for individual periods, and outputs to be extracted as they are completed at intermediate time periods, or reapplied to serve as inputs for the future time periods. In short, the DDEA methodology allows for a better understanding of how efficiently inputs were transformed into outputs at each sequential time period during the production process. The DDEA methodology falls short in identifying how the system transforms inputs into outputs, is comparative and not predictive, does not dynamically adjust for changing conditions, and is linear by nature.

The strength of SD modeling is gleaned by gaining insight into the model through its causal relationships, and determining how the system behaves (i.e. seeks a steady state) after a disturbance is introduced. Combining these causal relationships and feedback loops yields a predictive model that self-adjusts for changing conditions. Since the SD and DDEA methodologies are do diverse, I determined that the DDEA and SD frameworks were dissimilar technologies and thus unsuitable for combining.

DDEA is a framework that was built on the theory of productive efficiency. If a new methodology for evaluating productive efficiency within a SD framework was to be introduced, it was clear that this research would have to revisit the productive efficiency foundation which DDEA was built upon (Koopman, 1951; Farrell, 1957; Färe and Lovell, 1978; Färe and Primont, 1995; Färe and Grosskopf, 1996). Additionally, the theory of productive efficiency had to be evaluated to determine how well it corresponded to the theory of dynamical systems. The following questions emerged:

1. Do the production axioms defined by Färe and Lovell (1978) apply to production in a dynamic environment?
2. Can the traditional notions of productive efficiency (technical and allocative efficiency) be expanded into the dynamic environment?
3. Does the theory of dynamical systems support the evaluation of productive efficiency?

First, the production axioms (Färe and Lovell, 1978) were explored for compatibility and expandability. Since the production axioms are a set of fundamental assumptions that govern all productive behaviors, it was clear that these assumptions would fundamentally apply to the dynamic environment. However, there was not a perfect fit between the production assumptions employed in a static environment versus the assumptions that apply in a dynamic environment. Therefore the question of how the theory of dynamical systems will support productive efficiency had to be answered.

Samuelson (1947) identified two types of dynamical systems: (1) dynamic and historical; and (2) dynamic and casual. These system definitions allowed for the production axioms to be expanded into the dynamic realm. However, Samuelson's (1947) dynamical systems did not offer conditions necessary to satisfy expanding the production axioms, or the theory of productive efficiency to the SD framework because neither systems addresses the key concepts of equilibrium or stability. To address these concepts, a third type of dynamical system was proposed – dynamic, causal, and closed (Section 3.1).

The dynamic, causal, and closed system is important because it defines system relationships in an "essential way" such that the system brings results from past actions to influence or control future actions via a feedback mechanism. The feedback mechanism is the component that is missing in Samuleson's (1947) formulations that is required to expand the production axioms into the dynamic environment. As a result, Färe and Lovell's (1978) production axioms were expanded into a dynamic and causal, and dynamic, causal, and closed representations that would apply to SD based frameworks such as the dynamic productive efficiency model (Section 3.2).

The expandability of the traditional concepts of technical and allocative efficiency was explored next. Farrell's (1957) notion of evaluating the technical efficiency of a unit by comparing it to a corresponding production frontier (isoquant), and allocative efficiency of a unit by comparing it to a corresponding cost frontier (isocost line) in a static environment has withstood the test of time. However, while these principles apply to the evaluation of dynamic productive efficiency, the constructs in their original form, did not extend into the time domain.

To rectify this shortfall, the production and cost frontiers were expanded from $n$ input dimensions, to $n+1$ input dimensions, where time is considered the additional input dimension. By taking such action, isoquant and isocost planes emerge to form the dynamic efficiency plane (Section 3.4). If the unit falls on the isoquant plane, it is said to be technically efficient. If the unit falls on the isocost plane, the unit is said to be allocatively efficient. And, if the unit falls at the point of tangency of the isoquantic and isocost planes, it lies on the dynamic expansion line, and is both technically and allocatively efficient. The most efficient operating practices lies along this line. The purpose of the dynamic productive efficiency model is to define this line.

Section 3.5 develops the dynamic productive efficiency model. This model combines the SD hill-climbing optimization structure (Sterman, 2000) with the theories of productive efficiency (Farrell, 1957). This framework allows for initial conditions to be added into the model, and then through a series of causal relationships and feedback loops, is projected and optimized for future periods. While the hill-climbing optimization structure is not new, the application of productive efficiency concepts to this structure the structure is an outcome of this research.

The framework was tested against a widely used example from the productivity literature (Schmidt and Lovell 1979; Kopp, 1981) in Section 3.6. The example examines an oil-fired, steam-generating plant that transforms the inputs of capital, fuel and labor into electric power. The original solution employed a series of simultaneous equations to find the constrained optimization solution. The dynamic productive efficiency model was able to yield equivalent steady state results with the hill-climbing optimization structure when solving for both technical and allocative efficiency. However, Kopp's (1981) solution assumed an immediate adjustment time for each input variable. As such, the simultaneous equations solution did not show how the system adjusts from the introduction of initial disturbance until a time when the new steady state of operations is realized. However, this is not an uncommon characteristic of traditional productive efficiency methodologies. In fact, none of the productive efficiency technologies found in the literature assume an adjustment period. They simply solve for the new steady state of operations without clear direction how to navigate the transient period. The dynamic productive efficiency model did provide projected system benchmarks for the transient period.

Comparing the results of the dynamic productive efficiency model to the result of Kopp's (1981) solution proved to be a valuable way of validating the model with historical data. The next question that became apparent was, is this approach generalizable and scalable? The solution to the electric power production was "clean" as it had a pre-defined production function. To be generalizable and scalable, the model would have to be able to accept production function that is generated from real world systems. The purpose of Chapter 4 was to answer that question.

The implementation example showed that the dynamic productive efficiency model could be extended to a larger example with no pre-determined production function. Actually the system's production function becomes self-evident as the rates for the model are created through causal relationships. The lessons learned from the application are:

1. Variables to be optimized must be part of the objective function;
2. The variable to be optimized must be level variables, as defined by the hill-climbing optimization structures;
3. The production function can assume any form necessary to simulate the production environment;
4. The relative production variable, which effects the hill-climbing optimization structure, should only include factors that directly effect that variable.

I concluded from the implementation problem, that the dynamic productive efficiency model could be generalized to other efficiency problems that involve a transient period. Furthermore, there are no known constraints which would prevent the model from having a large number of hill-climbing optimization structures. However, as described in 1 above, the variables being optimized must be part of the production function, as it is pointless to optimize other model variables.

### 5.2.2 Hypothesis 2

*The new framework will provide insights into the performance of dynamic systems, plus provide additional insights about the drivers and levers of system performance.*

One of the strengths of most productive efficiency methodologies is that they are based on algorithms that can solve the combinatorial complexity problem. As a result, the best possible solution can be found from a large number of possible combinations. In contrast, SD models excel at solving the dynamic complexity problem that arises from interactions among system components over time. The problem of evaluating productive efficiency in a dynamic environment is that elements of both dynamic and combinatorial complexity are included. It was clear from the outset of this research that these two complexity concepts were going to have to be merged if this problem was going to be solved. I hypothesized that if these concepts were merged, that new insights about the performance of the system would be realized.

The dynamic complexity problem is solved with traditional SD models. When the hill-climbing optimization structure is added to the SD model, the simulation solves both the dynamic and combinatorial complexity problems.

Unlike traditional productive efficiency technologies, the dynamic productive efficiency model does not make historical comparison of various decision-making units to identify the best practice. Instead, the initial conditions are input into the simulation and a predicted system behavior is found. When the model is run without the hill-climbing optimization structure, the system behaves as it would without intervention from the decision-maker. When the dynamic productive efficiency model is included, the system will adjust to the optimal operating conditions for each time period.

This approach provides some significant insights over methodologies employed in the literature to date. First, instead of inferring that the system will behave historically, the initial conditions advanced through the system and time to predict future behavior. This is significant because when assuming that data will behave historically, one is discounting the possibility that once dormant feedback structures will become dominant in the future. Thus a simulation of the initial conditions introduced into a time-variant causal model can project future system performance.

Second, introducing the system's initial conditions into a SD model with the hill-climbing optimization structure, the predicted optimum conditions are found. Hence, this simulation defines the dynamic production frontier based upon expected future behavior. When comparing the results of the two simulation cases, one can extract how much productive efficiency can be achieved by changing operational concepts (Section 4.2.4). This is significant because this approach formulates the best possible operational concept for the system based upon the system's structure, policies, and decisions. In contrast, current methodologies generally select the best operating practices from the decision-making units being evaluated. Thus, less efficient decision-making units will be adjusted to the best operating practices, whether those best operating practices are efficient or not.

The causal relationships within the model provide another source of insight unique to the dynamic productive efficiency model. These relationships allow for decision-makers to determine the drivers and levers of good and poor operating practices. Heretofore, decision-makers were not privy to such insights with current productive efficiency technology. Thus system goals were established without understanding the potential unexpected consequences due to internal system interactions.

The human mind is good at relating causal events that are close in time and space. Unfortunately most causal linkages extend over large time expanses, and wide system breadth. To illustrate this concept, I used the Vensim Software suite to trace the causal factors and feedback loops that influenced the data level for each scenario. The results yielded 169 unique feedback loops for data 1 *D1*, 407 unique feedback loops for data 2 *D2*, 55 unique feedback loops of data 3 *D3*, and 554 unique feedback loops for data 4 *D4*. The feedback loops varied in length from 2 variables to 20 variables. The power of causal linkages and feedback loops cannot be underestimated when attempting to understand system behavior in a dynamic and complex environment.

The fact that the dynamic productive efficiency model yields different insights than methodologies to date should not be surprising. The model not only uses an approach that has not been used for this problem before, it uses a completely different set of data. Traditional productive efficiency methods search for patterns within the data, thus a lot of data must be collected for each input and output variable so that the variables and trends will become apparent. The dynamic productive efficiency model also requires a lot of data collection, but in a different way. Sufficient data must be collected on every system variable, whether the variables are input/outputs or not, so as to be able to glean an understanding of the causal relationships. Through these causal relationships the mathematical structure of the system becomes apparent. Every model variable must also contain an initial value. Therefore, while metrics concerning the inputs and outputs need not be collected, extensive data collection must occur to understand the systems and its initial conditions.

### 5.2.3 Hypothesis 3

*The framework developed will provide more complete and extensive information to the decision-maker as opposed to the information that can be gleaned through static evaluation means*.

The dynamic productive efficiency model has proven that it does provide more complete and extensive information for the decision-maker. However, while the information provided to the decision-maker is more complete and extensive it is significantly different than information provided by the more traditional approaches.

At the outset of this research, I believed that this information would be included in all of the following categories:

A. An evaluation of strategic and tactical policies;
B. An understanding of the causal relationships within the system;
C. A measurement of past system performance and a prediction of future system performance;
D. Identify the best system performance and operating practices;
E. Identify optimal performance targets;

As previously stated, the strength of SD modeling is the strong understanding of causal relationships within the system. By having a strong understanding of these causal relationships, future system performance can be predicted based upon a set of initial conditions. When the model is simulated without the hill-climbing optimization structure, the system behaves as it would without intervention from the decision-maker. When the dynamic productive efficiency model is included, the system will adjust to the optimal operating conditions for each time period.

The utility of this approach was demonstrated in Chapter 4 where four operational scenarios were tested. In each of these scenarios, a base case, where current operational practices were assumed, and an excursion case, where optimized operational practices were assumed and simulated. The output from these simulations proved to be significant. The following productive information were gleaned from the simulation:

1. Prediction of future performance;
2. Identification of the best operating practices;
3. Identification of target values the system should achieve at every time step during the transitional period;
4. When running two policies within the same scenario, a comparison between those policies.

While the above information could be extracted from the dynamic productive efficiency model as expected from the outset of this research, one measure – measurement of past system performance - was not achievable. This measurement was not achievable because the dynamic productive efficiency model is a forward-looking approach designed to help decision-makers navigate their organizations through transitional periods. Hence, the model does not consider historical data except in defining causal relationships within the model, and establishing initial conditions.

While the dynamic productive efficiency model does not address past behavior, the SD approach can with the Vensim Simulation Software. One of the possible solutions that were investigated for this research was using the model calibration in the Vensim optimization routine. This routine simply takes historical data collected for key variables, fits a line to the data, and then projects the data into the future. While this was an interesting approach, it failed to answer the question of how best to navigate the transitional period. This approach also does not lend itself to an easy comparison between decision-making units or policies. In short, while credible results can be gleaned from this approach, extracting patterns from data can be better-accomplished using approaches such as DEA, DDEA, and multi-variant regression. Since this approach did not answer the question at hand, it was rejected.

The dynamic productive efficiency model provides some unexpected information that cannot be obtained from other productive efficiency methods. While forecasting the amount of inputs required is commonplace among all models, the distribution of those resources with respect to time is not. For example, in three of the four scenarios in Chapter 4, the in-house employee to contractor mix was evaluated. The results of the simulations for these scenarios not only showed how many or each input was needed when, but also suggested the optimal policy of deploying them between the new data production and data maintenance functions.

Another unexpected outcome of the dynamic productive efficiency model was the prediction of which period to best implement new technology or processes to the system. As demonstrated in Chapter 4, this concept is an important management tool when considering when to introduce the next in a technology development spiral as an example. Knowing when and where to introduce new capacity and processes is a significant breakthrough in the productive efficiency field.

## 5.3 Recommendations for Further Research

This research has provided the basic foundation for evaluating efficiency in a complex and dynamic environment by bridging the gap between previously separate concepts. While bringing these previously detached concepts together may prove to be a significant contribution to the science of evaluating productive efficiency, it is time to take the next logical step by combining the technology developed in this research with object-oriented technology.

Object-oriented technology focuses on the concept that structures are comprised individual components with well-defined behavior. Each component may be part of several sub-systems. By combining object-oriented technology with the methodology developed in this research, a new technology will emerge that will help decision-makers and engineers plan and develop system-of-systems. This new technology will potentially allow decision-makers the ability to understand the complexities of their proposed system-of-systems through the causal relationships inherent within SD technology, and optimize their system-of-systems with respect to efficiency as a result of the dynamic productive efficiency model. The system-of-systems concepts are generally poorly modeled, thus there is no definitive method of predicting how the real world system-of-systems will behave when implemented. Taking this additional step will make great strides not only in understanding how a system-of-systems will interact, but how to achieve the maximum performance from such a system.

One of the conclusions of this research is that both DDEA and the dynamic productive efficiency models provide information for different problem sets. DDEA provides for an overall efficiency value in a dynamic, but steady state environment, while the dynamic productive efficiency model provides period-by-period efficiency assessments in a transient environment. One interesting exercise would be to insert the output from the dynamic productive efficiency model into the DDEA models, and in conjunction with the Malquist methodology to determine the overall productive efficiency during the transient period. Will the overall productive efficiency for this period be equivalent to the efficiency values derived from a period-by-period analysis?

Lastly, more research needs to be conducted to develop better methods for validating the future. While it will never be possible to validate a model that predicts a future system state, I believe that there are additional ways to mitigate any risk associated with these predictions. This research has taken steps to mitigate the risk by the known validation tests. This research has employed a wide-variety of behavior and results validation testing. As the system matures, validation continues by comparing actual system performance against the model performance. This will certainly make the model more valid as time progresses. However, the question remains, is there any other validation that could be accomplished to validate the future? This is an extremely important concept if the methodology developed by this research is going to be incorporated into an object-oriented framework for the development of system-of-systems architectures.

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