Dynamic Performance Measurement and Evaluation: Will Bridging Paradigms Lead to Improved System Design?[1,2]

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Abstract

Within the domain of systems engineering, conceptual frameworks are used to assist engineers, managers, and policy makers to determine new or modified system designs (Blanchard and Fabrycky, 2006). The designs are driven by requirements set typically by the users and are monitored using technical performance measures (TPMs). System designs are considered effective if they meet the pre-determined TPM values along with life-cycle cost and schedule targets. Therefore, in terms of measuring and assessing system design, one would expect synergy between the systems engineering and the performance measurement literatures. One possible synergistic thrust between these two bodies of literature is the modeling and assessment of dynamic system performance. There are many reasons for focusing on the concept of dynamic performance one of them being the effective management of the design process during change initiatives. In spite of the exceptional guidance available in the literature, the activities (e.g., the introduction of new technologies, the implementation of new training programs, etc.) that take place during transitional periods are often the most disruptive, and contain the furthest reaching performance and cost consequences, of any periods in the life-cycle of systems. One of the reasons for this unfortunate result is the failure of change techniques and methods to identify an efficient path of transition, from the old way of doing business, to a new performance paradigm. The organization's ability to master these transient periods is fundamental to achieving steady state operations more efficiently, thus reducing losses due to sub-optimal performance. An approach to that can directly account for dynamic performance measurement and evaluation during these transitional periods is the dynamic performance measurement model (DPEM) (Vaneman and Triantis, 2007). DPEM explicitly considers causal relationships within an operational environment and allows for the testing of different design alternatives. The primary objective of this paper is to present this approach and review it in relation to other dynamic measurement approaches found in the literature. Two examples (data archival and maintenance and the provision of social services within service supply chain) are discussed that illustrate the implementation of the approach. Another objective of this paper is to discuss why dynamic considerations can potentially lead to improved system designs. A tertiary objective is to outline specific future modeling and implementation challenges that require further research.

Key Words and Phrases: system design, dynamic performance.

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1.0 Introduction and Context

Within the domain of systems engineering, conceptual frameworks are used to assist engineers, managers, and policy makers to determine new or modified system designs (Blanchard and Fabrycky, 2006). The applications are diverse and range from hardware, to software, to transportation, to environmental, and to service provision systems. The designs are driven by requirements set typically by the users and are monitored using technical performance measures (TPMs) (e.g., reliability, maintainability, etc.) that map into the system architectures and functional system breakdowns. System designs are considered effective if they meet the pre-determined TPM values along with life-cycle cost and schedule targets. Therefore, in terms of measuring and assessing system design effectiveness, one would expect synergy between the systems engineering and the performance measurement literatures.

The performance measurement literature in the last three decades has focused primarily on advancing the modeling technology of performance measurement with key innovations pursued in econometric, mathematical programming, statistical inference methods for non-parametric frontier models and index number approaches (Fried, Lovell, and Schmidt, 2008). Furthermore, the applications of these modeling approaches has led to numerous applications ranging from accounting, to hospitals, to municipal hospitals, to world health organizations to name only a few (Fried, *et al.*, 2008). Nevertheless, the impact of this domain literature on the system engineering design literature has not received much attention. This is somewhat surprising given that the current North American productivity workshops (initiated at the School of Engineering and Applied Sciences at Columbia University in 1979) and the Journal of Productivity Analysis, the primary academic journal for the performance measurement and evaluation literature, were started at an engineering school. This lack of sufficient interface between the two domain areas was one of the key conclusions of the National Science Foundation workshop on Engineering Applications of Data Envelopment Analysis (DEA) (Union College, 1999).

One could ascribe different reasons as to why this has occurred. Focusing on these is beyond the scope of this document and has been dealt with elsewhere (Triantis, 2004). Suffice it to say that currently more researchers are attempting to find innovative ways to use the modeling perspectives found in the efficiency literature for engineering applications (Triantis, 2004). Nevertheless, the way of understanding and explicitly capturing causality in system structures and testing for alternative design configurations have been important points of departure from what engineers are practically involved with on a daily basis and what applied performance measurement studies have focused one.

The term *causality* in this document refers to the explicit representation of cause-and-effect relationships that theoretically or empirically are understood to exist between components within a system. This issue is critical to system analysis because it can help identify root causes of system performance and allow key system or process components to be studied and adjusted for future performance enhancements. This is not to imply that causality is not considered in the performance measurement literature. Causality in this literature is primarily understood in the input/output representation of production systems and/or in the relationships between performance and environmental or managerial considerations. Furthermore, testing alternative design configurations is a primary concern in the design of experiments literature (Evans and Lindsay, 2008) and it an issue that is central to engineering mindset. Creating a bridge between this mindset and the performance measurement literature was one of the key recommendations of the NSF workshop on Engineering Application of DEA (Union College, 1999).

These two points, i.e. of causality and testing can be linked to another concept that is being investigated in the performance measurement literature. This is the notion of dynamic performance measurement (Stefanou, 2006). In this paper, a definition of dynamic performance is provided that takes an endogenous view of system performance and allows for the explicit representation of causality and for testing of different design configurations. This definition is linked to a methodological approach for measuring and evaluating dynamic performance (Vaneman and Triantis, 2007). Two examples illustrating the application of this approach are briefly included in this paper. Another objective of this paper is to discuss how dynamic considerations can potentially lead to improved system designs. A tertiary objective is to outline specific future modeling and implementation challenges that require further research.

There are many reasons for focusing on the concept of dynamic performance one of them being the effective management of systems during change initiatives. The literature is rich with change techniques and methods that provide guidance to organizations seeking change. However, in spite of the exceptional guidance available, interventions (e.g., the introduction of new technologies, the implementation of new training programs, etc.) that take place during transitional periods are often the most disruptive, and lead to the furthest reaching performance and cost consequences, of any periods in the life-cycle of systems. One of the reasons for this unfortunate result is the failure of change methods to identify an efficient path of transition, from an old way of doing things, to a new performance paradigm. The organization's ability to master these transient periods is fundamental to achieving steady state operations more efficiently, thus reducing losses due to sub-optimal performance. This links back to the necessity of designing systems (e.g. enterprises) to efficiently and effectively accommodate change interventions.

There are a number of disclaimers that are in order at this junction. First and foremost, it not the intent of this document to necessarily cover all the possible perspectives of the performance measurement literature. The theoretical and application main is too large to cover in a single document. Rather the intent is to take a more narrow perspective and consider the viewpoint of a manager, engineer, economist (decision makers and analysts) who begin their discovery and modeling from an efficiency perspective (Fried *et al.*, 2008) and are looking to bridge to the decision makers and analysts who are using dynamic modeling paradigms, for example system dynamics (Sterman, 2000). It is the hope that the discussion of the issues, model, and examples presented in this document will initiate a dialogue among different domain specific perspectives with the objective of providing engineers and managers integrated viewpoints that lead to more effective designs. The initiation of this dialogue will hopefully lead to the adaptation of complementary approaches that provide more comprehensive frameworks.

The rest of this paper is organized as follows. A brief overview of the literature is provided in the next section. The notion of dynamic efficiency is presented in Section 3. The Dynamic Performance Evaluation Model (DPEM) (Vaneman and Triantis, 2007) is discussed in Section 4 whereas a brief overview of two examples where the DPEM framework has been applied is the focus of Section 5. Section 6 concludes and discusses future research issues.

2.0 Background

There are various perspectives of dynamic performance measurement that have been discussed in the literature (Shephard and Färe (1978), Hackman (1990), Färe, Grosskopf, and Roos (1992), Nemoto and Goto (1999, 2003), Sengupta (1995, 2005), Färe and Grosskopf (1996), Silva and Stefanou (2003, 2006), Stefanou (2006), Vaneman and Triantis (2003, 2007), Emrouznejad and Thanassoulis (2005), Armiteinoori (2006), Wang and Huang (2007), Chen (2008) and Korteleinen (2008)). The majority of these approaches are discussed by Stefanou (2006) and it is not the intent of this paper to cover these different perspectives in depth. It is important to note that at least two articles in the literature deal with the axiomatic framework of dynamic production. The first by Hackman (1990) where the production system is modeled as a collection of interrelated production activities that consume exogenous materials and services to produce final products. The key time varying elements of this research include intermediate product transfers, inventory and material balances, and capacity limits of service consumption. Dynamic production functions are introduced that map time varying input consumption into outputs. The second by Vaneman and Triantis (2003), maps production axioms into system behaviors.

Nevertheless, if one wanted to provide a crude categorization of this body of literature there is the activity based approach (Koopmans, 1951) to measuring efficiency over time that is based on a linear structural representation (Shephard and Färe (1978), Sengupta (1995, 2005), Nemoto and Goto (1999, 2003) and Färe and Grosskopf (1996), Emrouznejad and Thanassoulis (2005), Armiteinoori (2006), Wang and Huang (2007), Chen (2008)). There are variations of this work that includes but not limited to network representations that address inter-temporal substitutions between input, outputs and intermediate outputs, the specification of a smooth cost and revenue functions, the incorporation of market demand and input uncertainty over time, and building discrete time varying mathematical programming models as they relate to dynamic optimization. Related to this approach is the use of the Malmquist productivity index to capture both efficiency and productivity changes over time (Färe, Grosskopf, and Roos (1992), Korteleinen (2008)).

One of the new directions in the literature focuses on a non-parametric dual-based revealed preference approach to the dynamic theory of production in the context of an adjustment-cost technology and inter-temporal cost minimization (Silva and Stefanou (2003)). They consider capital as a quasi-fixed factor that is managed as an asset where rapid expansion or contraction of the stock of capital is accompanied by adjustment costs. They explicitly address the dynamics in the production technology specification as an adjustment cost in the form of the properties of the family of production possibilities set with respect to dynamic factors. Based on this theoretical framework, Silva and Stefanou (2007) develop nonparametric dynamic measures of technical, allocative and economic efficiency for the short and long run. The efficiency measures proposed in Silva and Stefanou (2007) are temporal in nature by describing the degree of efficiency of the firm at a particular point along its adjustment path.

Nevertheless, these approaches do not explicitly consider how complex interactions among key production variables can potentially lead to observed behaviors. The explicit consideration of these interactions as well as assumptions pertaining to causality between variables leads to a more "micro" representation of the production or transformation process. In an input (resource) output (product/service) world the notions of interaction and causality lead to a more in-depth understanding of how scarce resources are transformed into outputs and/or services. The perspective of opening the input/output black box is not new in the performance measurement literature. In the late, ninety seventies the notion of an "engineering" production function (Eide (1979)) focused on this view. Transformation/production functions were represented as a system of detailed equations covering physical, economic and organizational relationships. The intent of the dynamic performance evaluation model (DPEM) (Vaneman and Triantis, 2007) is to build on this disaggregate representation and to capitalize on the notion that is widely accepted in the system dynamics community that structure leads to system behavior.

The definition of "structure" within this perspective is based on capturing the physical, decision making and organizational realities of the enterprise or system. This is not conceptually different from how modelers defined engineering production functions. This view attempts to understand "how" the production or transformation functions manifest themselves. In the performance measurement literature the use of the term structure is used in terms of defining the concept of "structural efficiency" and is defined originally by Farrell (1957). This concept broadly measures to what extent an industry keeps up with the performance of its best practice firms. One interpretation of this notion is to what extent the industry production level is optimally allocated among firms. This constitutes a macro and short-term viewpoint of the notion of structure.

Nevertheless, the micro perspective of structure allows one to explicitly deal with at least two fundamental issues of production systems. First, the explicit inclusion of feedback mechanisms that is always part of production processes. Second the explicit inclusion of delays, which is another key characteristic of production systems. These delays are typically either material or information delays. For the performance measurement approaches (econometric (Greene, 2008) and mathematical programming approaches (Thanassoulis, Porter, and Despić, 2008) delays are typically included as lagged variables even though the distinction between material and information delays is not always apparent.

Understanding the micro structure of the system or enterprise, allows for a better appreciation of its behavior. The mapping of the production axioms (Färe, Grosskopf, and Primont, 2007) to observed system behaviors (Sterman, 2000) was first attempted by Vaneman and Triantis (2003). This mapping provides a glimpse at how specific production axioms can hold for certain behaviors. Realizing that each production axiom can only hold in specific system behaviors allows one to appreciate the implications that production assumptions can have in modeling performance.

3.0 The Definition of Dynamic Efficiency[3]

The following definitions are built on the initial framework provided by Farrell (1957). *Dynamic productive efficiency* is a measure of a system's ability to convert inputs into outputs at a specific time *t*, during a transient period, such that either the largest possible outcome is achieved given a fixed set of inputs (output maximization principle), or the least possible inputs are employed given a fixed set of outputs (input/resource minimization principle) at the minimum cost of production. This is consistent with the fundamental concepts of efficiency found in the performance measurement literature, i.e., of technical (either input reducing and/or output increasing) and allocative efficiency (the degree to which the enterprise is minimizing the cost of production). Dynamic productive efficiency has two important characteristics that distinguish it from the traditional notion of static productive efficiency. First, the element of time is introduced. The importance of time is realized during a transient period, as the projected system performance is compared against a dynamic production frontier or another decision-making unit (DMU) (Charnes, Cooper, and Rhodes, 1978) for the same time period. The production frontier is defined as the boundary of the production possibility set where producers optimize by not wasting resources, by maximizing throughput, and minimizing cost. Second, a disturbance (i.e., a change in inputs, outputs, or processes that triggers a change in the ability of the system to convert inputs into outputs) is introduced into the system that causes it to seek a new equilibrium level.

[3] Adopted from Vaneman and Triantis, 2007.

As can be observed from Figure 1 one can have many transient options. By inspection, transient option 2 is more efficient than transient option 1. The DPEM provided later in this paper describes how the optimal path (transient option 2) is found. For the purposes, of this discussion it is assumed that the transient option 2 is a representation of a production frontier over time.

<Figure 1 approximately here>

In static productive efficiency evaluations, data for a single DMU can be generally collected over time, with the assumption that the system conditions are the same at each data collection point, thus allowing data collected at times *t-1* and *t* to be treated and compared equivalently. In dynamic productive efficiency, the assumption that all time periods are equivalent does not hold (thus data collected at time *t-1* cannot be compared with data collected at time *t*). Making such an assumption under normal conditions will always yield a higher efficiency value for the data collected at *t* assuming that the behavior of the system is depicted in Figure 1. Therefore, what kinds of comparisons are meaningful?

Points α and β are data points collected at the same time *t*, and therefore can be compared in terms of efficiency performance evaluations. Examining points α and β more closely (Figure 2), the traditional isoquant and isocost lines of microeconomics are revealed for a single time period. Point β lies at the intersection of the isoquant and isocost line, thus is deemed both technically and allocatively (cost minimizing) efficient with respect to point α (Farrell, 1957). Point α is initially located to the northeast of the isoquant and is deemed technically inefficient. Under constant returns to scale, for point α to be technically efficient, either inputs must be reduced by a factor of $0\alpha'/0\alpha$ to produce the same level of output, or outputs must increase by a factor of $0\alpha/0\alpha'$ while holding the inputs constant. To become allocatively efficient the cost of point α must be reduced by $0\alpha''/0\alpha'$. If point α is improved by a factor of $0\alpha''/0\alpha$, it will attain the same overall productive efficiency score as point β (Farrell, 1957).

<Figure 2 approximately here>

Figure 2 depicts a single time period. As time progresses, the representation of Figure 2 repeats itself for different (in this example increasing) levels of output, input usage, isoquant and isocost lines. The dynamic efficiency expansion (Figure 3) elaborates the concept further. As in Figure 2, this Figure portrays two input axis x_1 and x_2, and adds a time axis *t*. In a continuous time environment the level of output *y* is represented by an isoquantic surface. Likewise, in continuous time, the isocost lines are also represented as the isocost surface.

<Figure 3 approximately here>

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 β in Figure 2). In a continuous time environment overall productive efficiency is achieved along a line (a series of points of tangency that are infinitesimally close together through the time continuum) where the isoquant and isocost planes are tangential. This line is known as the *dynamic expansion line*[4]. The dynamic expansion line represents the most efficient (overall productive efficiency) path to traverse during a transient period $[t_0, t]$. In the following section, a system dynamics (SD) (Sterman, 2000) methodology that is designed to find the dynamic expansion line is presented.

4.0 The Dynamic Performance Efficiency Model (DPEM)[5]

The DPEM can have various representations that correspond with the given problem. However, one of two basic forms (input-decreasing or output-increasing) serves as the foundation for all DPEMs since the concepts of input reducing or output increasing performance are well established in the efficiency literature. The input-decreasing model holds the level of output required constant and minimizes the input variables. In this case, the level of output required can be interpreted as the system goal. The output-increasing model holds the input variables (i.e., system parameters) constant and maximizes the output variables (i.e., system output or system goal). For the sake of brevity, the DPEM for the input-decreasing single output case is described in the remainder of this section. For details on the input reducing multiple output and output increasing cases and for the computation of allocative or cost minimizing efficiency, refer to Vaneman (2002). Nevertheless, the output increasing case is similar conceptually to the input-reducing case.

The generic DPEM for the input-decreasing case is shown in Figure 4. In its most basic form, this model is governed by three feedback loops – the system effect loop, the input x_i adjustment loop, and the input x_i search loop.

<Figure 4 approximately here>

The purpose of the system effect loop is to represent the effects of the objective function and system constraints on the optimization structure. The input variables for the model are represented by the level variables x_i. The objective function for the model is the system's production function $y=f(x_i)$. The production goal y^* behaves as in a typical goal seeking structure. However, it represents a form of a constraint. The production goal feeds into a negative feedback loop and is designed to ensure that the optimal value of the inputs x_i lie within a finite interval such that $0 < x_i < \infty$. The production goal keeps the system in balance through a variable that calculates the discrepancy (i.e., the discrepancy comparison variable $\tilde{y}$) between the current state of the objective function y_p and the production goal y^*.

[4] For illustrative ease, the dynamic expansion line is represented as a straight line in Figure 3. In reality the dynamic expansion line will most likely not be a straight line, by vary non-linearly in n-dimensions.
[5] Adopted from Vaneman and Triantis (2007).

The production goal is compared against the production function through the discrepancy comparison variable $\tilde{y}$. When comparing the production function to the production goal, the following relationship is used:

$$\tilde{y} = \frac{y^*}{y_p} \tag{1}$$

The discrepancy comparison variable $\tilde{y}$ is one of the key drivers in determining whether the level variable should be increased or decreased. Since a system may have many production goals the discrepancy comparison variables must be constructed such that the resulting units are dimensionless. When a system has *m* multiple production goals are present, their dimensionless nature allows for their effects to be combined.

The hill-climbing optimization structure encompasses two feedback loops – input x_i adjustment and – input x_i search. Three primary variables compose these feedback loops. As with any SD model, the level variable serves as the centerpiece of the system and represents the state or condition of the system, and is the initiation point for any simulations. In the input-decreasing case, the level variables are the inputs that are minimized. The level variables in the input-decreasing case are defined as (Sterman, 2000):

$$x_i = x_{i_0} + \int_0^t \Delta x_i dt \tag{2}$$

Where, x_{i0} is the initial value of the input variable at the beginning of the transient period. As seen in (2), the level variable x_i is atypical of level variables commonly found in SD models because it only contains an inflow rate. The reason for this is that the hill-climbing optimization structure is designed to find the optimal values, thus is an artifact (i.e., an algorithm that is used for a specific computational purpose, but would not be found in a causal mapping of an organizational structure) of the model. The level variable is adjusted by the structure of the hill-climbing algorithm.

The level variable is the link of the hill-climbing algorithm with the feedback loops that represent the physical system's structure. As previously discussed, the input x_i feeds directly into the production function which is used to calculate the system's current level of performance. The level variable is adjusted by a rate variable (known as the input change rate (Δx_i)) which determines the change in the system's state due to optimization that is driven by the system's production function. The input change rate adjusts the level by considering the previous input level x_i, the target input x_i^*, and the adjustment time *at*. The input change rate is defined as (Sterman, 2000):

$$\Delta x_i = \frac{x_i^* - x_i}{at_i} \tag{3}$$

The adjustment time at_i is the time required to place the input variable x_i into equilibrium (i.e., to achieve a new steady state) at its present rate of change. The adjustment time is defined as:

$$at_i = f(t) \tag{4}$$

The target input variable x_i^* is an artifact that is introduced into the hill climbing optimization structure to aid in searching for the optimal value of x_i. The variable considers the current state of the system (i.e., the value of the input variable x_i) and the effects of the system constraints κ_{sy} on the system (e.g., system reliability), and the influence from the discrepancy comparison variable $\widetilde{y}$. The target variable is defined as:

$$x*_i = x_i \widetilde{y}_g \kappa_{sy} \tag{5}$$

When working in tandem, the three feedback loops form a unimodal function[6] (Wagner, 1969) where there is a unique optimal value for x_i over the interval $0 < x_i < \infty$. The purpose of the input adjustment loop is to govern the rate at which the gap between x_i and x_i^* is closed. The system effects loop applies the external pressure to cause x_i to seek its optimal value. If $\widetilde{y}_g > 1$, the system effect loop will cause $x_i^* > x_i$ and hence put a pressure on the input search loop to increase the input variable x_i. If $\widetilde{y}_g < 1$, the system effect loop will cause $x_i^* < x_i$ and will put pressure on the input search loop to decrease the input variable x_i. When $\widetilde{y}_g = 1$, the system effect loop will apply no further pressure to the input search loop, and will cause $x_i^* = x_i$. When this occurs the optimal conditions have been achieved.

There are a few caveats to this approach. First, a sufficient number of simulation iterations must be made to ensure the model achieves it global maximum value. Since it is possible for the system to have many local maximums, the only way to ensure that the global maximum is found is by repeated simulation runs and varying the time steps used in the simulations. Second, as in the real world, there is no guarantee that the model will converge. If it does converge, the achieved state of the system may or may not be the optimal value even after a sufficient number of simulation iterations.

The multiple input and multiple output representations of the dynamic productive efficiency model (DPEM) are discussed in detail by Vaneman (2002) and Vaneman and Triantis (2007). The implementation of the DPEM requires that one first define the system structure, the resources that will be optimized, and the production goals during the technology implementation phase. Once this is completed, then the use of the DPEM within the system structure is straightforward.

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[6] A uni-modal function has one mode (usually a maximum, but could have a minimum, depending on context). If f is defined on the interval [a, b], let x^* be its mode. Then, f strictly increases from a to x^* and strictly decreases from x^* to b (Wagner, 1969).

5.0 Two Illustrations

5.1 The Introduction of New Technologies: Data Production, Maintenance and Aging[7]

Adopting and introducing new technologies into an organization often brings unexpected consequences. Unrealistic mental models of the decision-makers, and the failure to adequately, and accurately, assess the impact of the system's concept of operations often leads to unforeseen losses in productivity, degradations in quality, and unexpected costs for most new technology efforts. These losses usually translate into increased system life-cycle costs. As a consequence, many efforts never realize the full performance potential of the new technologies they choose to adopt. Figure 1 depicts the artificial plateau organizations may experience when the technology they adopt fails to achieve each its full potential.

Consequently engineers and managers need to assess and plan for the introduction of new technologies as it pertains to the implementation phase. The technology implementation phase is the period between a technology's development/procurement and operational phases (Vaneman and Triantis, 1999). One of the key hurdles of this phase is finding the optimum operating scenario (system configuration and production processes) from a large number of technological possibilities. This problem was the primary driver of the development of the DPEM. This structure offers a mechanism that provides the decision-maker with an optimal path (i.e., an implementation road map with goals for each time period) to follow during the technology's implementation phase. Hence, the objective is to reduce losses that naturally occur during the implementation phase by defining the more efficient path as depicted in Figure 1.

The organization that was studied is in the business of compiling and disseminating information via an Internet-like media. Data population was planned to occur over a ten-year time horizon. Our research evaluated the organization's plans to implement a system that will produce the desired amount of information, and sought to define more efficient and effective implementation procedures through alternative system policies.

While planning for the implementation of the new technology, the organization used a spiral model extending six years, with technology (primarily workstations) installations at the beginning of each year of the cycle. To have sufficient capacity to produce and maintain 12,000 cells of data within ten years, 1,550 workstations would be required. The spiral model planned for 225 workstations to be installed initially, with 225 workstations being installed at the beginning of years one through five, and 200 workstations added at the beginning of year six. No additional workstations or re-capitalization was envisioned or planned after year six.

5.1.1 Data Collection

[7] Adopted from Vaneman, 2002.

The data for this study was collected over a 30-month period at four geographically disperse offices of the organization. During this data collection period, system stakeholders who understand the system, its input and output elements, processes, and critical structural links were interviewed and were requested to provide data. The interviews (which assumed the form of informal discussions and e-mail exchanges) had the purpose of collecting system goals, actual and projected metrics, and to gain an insight and understanding into organizational policies, cultures, and interrelationships among system components.

More specifically the data collection was focused in four fundamental areas: 1) Identifying the system boundaries; 2) Understanding the system structure; 3) Defining interacting variables; and 4) finding the values of parameters. The data sources available for the variables used in the study were many and varied. Various stakeholders provided the data supporting specific variables. However, this approach was problematic because: (i) the production concepts of the organization were fluid, thus data that was perfectly valid yesterday, is outdated and irrelevant today; (ii) since in virtually all cases the information provided were projections of resources the system used and data with respect to the system output was subject to each individuals understanding of the concept of operations and the technology being employed; and (iii) in some cases, data supporting various political agendas was introduced. The data was de conflicted by comparing the multiple sources of data against each other and against the concept of operations (which in most cases was informal due to the fluidness of the production system processes), and against the expected system behavior. Unusual observations that would have severely skewed the model results with respect to system behavior and magnitude of the performance estimates were discounted.

5.1.2 DPEM Implementation

One of the areas we applied the DPEM was to evaluate the optimum time to insert new workstations. This issue represents a significant departure in engineering management as the spirals are commonly dictated by budgetary and time constraints, and not by the actual need of the system. The organization's actual production processes were modeled by identifying its causal elements and linkages (Vaneman, 2002).

An example of the implementation of the DPEM is provided in Figure 5. This DPEM structure links to a production structure that represents how new data are created and how they age over time. In the base case scenario there is no maintenance of the data whereas in the modified or "excursion" case the data is maintained. The optimization structure of Figure 5 takes the form of the hill-climbing optimization structure discussed in Section 4. The most significant difference between the generic structure presented in Section 4, and the hill-climbing optimization structure is that the production function defined here is based on the causal relationships defined by the organization. In this case study, the production function *(Dpu)* is the amount of output that can be theoretically produced by the data production rate *(DPRu)*, the data maintenance rate *(DMRu)*, and where applicable the special data production rate *(SPRu)*. The data production and data maintenance rates in this research assume a Cobb-Douglas (1928) production function where the parameters are estimated empirically.

<Figure 5 approximately here>

The Cobb-Douglas Production function (Cobb & Douglas, 1928) is used in this study because it allows for the contribution of the key drivers to be considered in the same equation. Two important assumptions accompany this production function. First, all in-house production is generated as a result of the production function. Thus, the production function does not account for managerial overhead. Nor does the basic Cobb-Douglas Production Function include the addition of contractor production. Contractor production is not included in the specification of this function because the contribution of the contractors to the system is not dependent on in-house employees. The second assumption is that any change to the elasticity exponents will result in a proportional change to the input variables, and if the sum of the elasticities changes the output will also change.

The variables shown with the employee hill-climbing optimization labeled as be "theoretical" were added to the model for simulation convenience. During the verification of different scenarios associated with different data types, it was discovered that after all new production was completed that the contractors went through a ramping down period as they were moving to the data maintenance task. While the ramping down period generally lasted less than ten iterations, additional new production went through the system. This had dramatic, and erroneous, effects on the calculations for employees, workstations, and contractors. This behavior did not mimic real world production as the real world system has a finite goal of 12,000 cells. The introduction of the artificial construct theoretical maintenance *DTMu* forces all resources to be shifted to data maintenance once data production was completed.

5.1.3 Design Implications

Figure 6 depicts where each technology spiral should occur as determined by the DPEM, and where it occurs with spiral implementation centered on budgetary cycles. Using the results from the DPEM, the first technology spiral occurs after period 24, the second after period 48, and the third (minor) spiral occurs after period 60. Note, that the DPEM does not recommend a step-increase in workstations during each spiral, but instead suggests a gradual implementation during the entire spiral. The infrastructure required to perform all maintenance after the first data decomposition is realized is handled by the initial system set-up, thus few additional resources are required between periods 12 and 24. By period 24, the maintenance requirement doubles which prompts the second spiral. At period 48 the amount of data maintenance required prompts the system to seek a new steady state, thereby initiating the third technology spiral. At period 60, a new steady state is sought again. Period 60 corresponds to the period when one-half of the production goal is realized. The fourth spiral begins with a slow but continuous influx of new workstations until the full complement of 1,550 workstations is realized at period 113.

<Figure 6 about here>

There are two primary benefits of defining technology implementation spirals as suggested by the DPEM. First and foremost, technology is introduced into the organization in a planned, just-in-time fashion. Thus excess capacity and the cost associated with maintaining that excess capacity is minimized. Second, considering Moore's Law, workstations will increase in computational speed as time increases. The slower implementation rate means that state of the art workstations will be installed throughout the entire implementation phase, and not just to the end of arbitrarily defined spirals. Considering the last workstation installed under the DPEM schedule will be more than 4 years after the last workstation installed under the arbitrarily defined model, the technology introduction differential is significant.

5.2 The Service Profit Chain[8]

The computation of dynamic efficiency measures is illustrated through the application of the DPEM approach to evaluate service training operations in a service-profit chain (SPC). As service firms account for a substantial part of the output of a number of economies, one can say that evaluating service delivery operations and the impact that the delivered services have on the behavior of service recipients is more relevant than ever in the new global market. Particularly, with the advent of e-commerce, evaluating services, and investigating approaches that can help firms identify service features that not only satisfy customers, but that also produce repeated business and ultimately increase the bottom line is ever more important.

More specifically, the Service-Profit Chain (SPC) framework (Heskett *et al.*, 1994) brings together several operational components, customer perceptions, customer behavioral intentions and customer loyalty to evaluate service operations. The components of the SPC are representations of the actual input-output transformation that occurs within the enterprise's service chain. Feedback mechanisms are included in the chain that allow for the optimization of operational attributes during the transition period. This in turn allows for the dynamic performance evaluation of the long-term impact of operational investments. The optimization of operational investment is accomplished by incorporating a hill-climbing algorithm as part of the DPEM in a system dynamics model of the SPC. The hill-climbing algorithm evaluates the current operational state of the SPC system and compares it to specific

[8] Adopted from Pasupathy, 2006.

operational performance goals to determine the gap that can potentially lead to additional investment interventions.

The investment in operational attributes that are driven by externally defined performance goals, leads to the assumed structural transformations within the SPC chain (Figure 7). This is analogous to explicitly representing the physical transformations in a production environment which in most cases is abstractly represented by the production function. In this case, changes in operational attributes increase both service quality and expenses. Increases in service quality lead to increases in overall satisfaction, intention to return, referrals and an increase in the customer base. Increases in the customer base increase both the revenues and market penetration whereas an increase in expenses that result from increases in operational attributes leads to a decrease in the enterprise's revenue base. The formalization of these structural relationships has been documented elsewhere (Pasupathy, 2006) and for brevity purposes will not be provided here. However, in a classical input/output efficiency representation, the operational attribute can be perceived as a critical input whereas, service quality and customer satisfaction can represent intermediate variables and customers served can represent typical output variables.

<Figure 7 approximately here>

The research case study was conducted at the national headquarters of a social service organization in Washington DC. The case study concentrated on Health & Safety training of First Aid and CPR (cardiopulmonary resuscitation) courses. The Health & Safety Services Department has a total of 12 million enrollees (or course takers or customers) per fiscal year, out of which six million enroll in First Aid and CPR training alone. The organization has approximately 1000 field units across the United States providing services in the community. First Aid and CPR is one such service where the course is taught in the community for a fee. An example of a policy decision related to this operational attribute follows. Field unit A of the organization has a policy establishing that they should register no more than ten customers in each course offering. This field unit is interested in knowing whether this is a sustainable policy. Is their customer base poised to increase? How do they need to phase in their investments in increasing course offerings over time?

Field unit A of this organization is large and complex, with many departments and functions interacting. Addressing the policy issues related to operational investments involves understanding various organizational aspects like financial management, capacity creation, service delivery, market research, etc. Knowledge of the entire enterprise requires the understanding of the operations of several departments and no one person has a holistic view to address the policy questions identified previously. However, large amounts of data are being collected year after year by the field unit and its headquarters. These large amounts of data can be used along with the model and the proposed methodology to answer key policy issues.

For example, the field unit knows that the main competitor in the market provides a similar course for $60 (lower when compared with the field unit's course fee of $65) but they believe the contents are of lower quality. The relative value[9] of the course offered, was rated at 78.7%. Since service quality[10] itself was not a measured item in that study, it will be set arbitrarily at some percent (initial condition) and the changes will be modeled and analyzed within the context of the SPC model created in this research.

5.2.1 Data Collection

In executing the SPC model created in this research it is assumed that the unit of analysis will be a field unit. Field units have Health & Safety instructors employed to teach the courses and train the people. They use books, videos and other materials for providing these courses. Typical settings for teaching are the field unit office, schools and other office buildings. A lot of data is collected around this operation by the field units themselves and the enterprise's headquarters. Customers are surveyed about their perceptions. Responses to surveys were aggregated at the field unit level. Several additional sources of data were used for the purpose of this case study that includes the following: a) Financial profile: This data source has all data pertaining to the finances of the field unit, like revenue, expenses, investments made in specific attributes. Data was available for 980 field units; b) The Service delivery and demographic profile: This profile has data on enrollees (customers), number of courses and instructors, personnel, demographic variables, etc. Data was available for 991 field units; c) The Customer profile: This profile is available through a program that has been implemented in the past. Data is available on personnel efforts and on customers like perceptions and satisfaction, behavioral intentions and customer loyalty. 406 field units participated in the program, surveyed their customers, hence data was available from 250,000 survey responses.

5.2.2 The Computation of Dynamic Efficiency

Customers per course is the operational attribute where investments can be made by increasing the number of course offerings. Offering to register certain number of customers per course has trade-offs. On one hand, having more customers per course, reduces the operating expenses, having to pay fewer instructors, etc. But on the other hand, this policy provides lesser flexibility in terms of number of locations and schedule options where courses can be offered. This reduces the ease of taking the course for customers. Further, each course sitting can be perceived to be more crowded. Over time this can

[9] Relative value is defined as the value perceived by the customer based on the quality of the service received for the price paid in comparison to the quality of similar service offered by competitors for their price (McDougall and Levesque, 2000).

[10] Service quality is the quality of the service provided by the organization to the customer and constitutes a set of items. Service quality is measured as it is perceived by the customer using these items on a survey instrument (Pasupathy, 2006).

reduce positive perceptions of the course. The search algorithm can help determine an operating steady state.

The search algorithm determines the discrepancy by comparing the current customers per course against the target customers per course to set the target number of courses. The target number of courses at any instant determines the change in the number of courses necessary to attain the steady state. This structure is shown in Figure 8. The efficiency score is computed as a ratio of the target customers per course to the current customers per course. The variables shown in the background (changes in courses per customer, customers and expense) are part of the overall SPC model. For simplicity of representation, the overall SPC structure is not discussed here, see Pasupathy (2006) for a detailed explanation. Nevertheless, the target customers per course can be represented either as an externally determined parameter as in the case of this research or as a value of that one can obtain from a previously estimated production function (Vaneman and Triantis, 2007). The value of the current customers per course is determined by the structure in Figure 7 where the transformation of resources into outputs is structurally represented as a stock and flow model (Sterman, 2000).

<Insert Figure 8 approximately here>

5.2.3 Dynamic Efficiency Results

The dynamic simulation model for a specific field unit was run for a twenty year time horizon with a one year time step. The target number of courses that is driven by the desired number of customers per course (ten in this case) has been set externally by a field unit decision maker. The key operational attribute that can be perceived as an input to the service-profit chain is the number of courses. The *number of courses* to be offered (measured in Courses, shown as Crse in Figure 9) follows almost an S-shaped curve with the lower leg rising more abruptly and attaining a steady state. The *change in number of courses* (measured in Courses/Year, shown as Crse/Year in Figure 10) follows a skewed bell-shaped curve and is positive for the entire time horizon indicating the need to increase course offerings (i.e., an intervention by adding courses) every year for the next 20 years. The behavior starts to gradually rise from the initial value of approximately 50 courses per year to reach a maximum at the sixth year. For the first six years, courses are added at an increasing rate (every subsequent year more courses are added than the previous year). After the sixth year, the behavior drops to reach a steady state by the 20th year. Thus from the sixth year onward, courses are added at a decreasing rate (every subsequent year lesser courses are added than the previous year). In terms of dynamic efficiency that is represented in Figure 11, during the first two years there is a decline in the overall efficiency of the SPC. This can be attributed to the adjustments that the system needs to make in terms of requisite number of courses and the consequence this has in terms of service quality, overall satisfaction and the unit's customer base. What is important is that after year two there is a steady increase of efficiency performance with it asymptotically approaching the value of one during the later years. The steady state values for key variables in the SSC are given below in Table 1.

<Insert Figure 9 approximately here>

<Insert Figure 10 approximately here>

<Insert Figure 11 approximately here>

<Insert Table 1 approximately here>

5.2.4 Design Alternatives

For this specific simulation, the course offerings need to increase continuously from the current 220 courses to 1,765 courses in 20 years following a skewed bell-shaped curve shown in Figure 9. From a policy and decision making point of view there are a number of important questions that need to be addressed as part of the sensitivity and policy analysis associated with this model. How do the increase in customer base (market penetration captures the increase in the customer base) and course offerings compare against changes in community population and the environment in general. Further, what does this mean in the context of what is generated as a surplus (revenue – expenses) and a marginal rate of return given that additional expenses will be incurred as a function of the increase of the number of courses? Will the decision makers tolerate the short-term decline in efficiency performance? Will the increase in the number of courses actually lead to desired levels of service quality and overall satisfaction? If this is not the case, then should the decision-maker then focus on investments in other operational attributes?

More fundamentally, is the policy of no more than ten customers for each course offering sustainable? The answer to this question depends on how the field unit weighs its options. Based on the analysis, the field unit can currently cover all its expenses by the revenues generated. Investing in more course offerings, increases market penetration and surplus but at the same time brings in decreasing marginal rates of return which is something that decision makers may not find reasonable (Pasupathy, 2006).

6.0 Conclusions

Within the context of system design, the dynamic productive efficiency model (DPEM) offers multiple benefits. For new system designs or system re-designs it allows for the definition of customer requirements that are in alignment with performance goals. Achieving these performance goals determines the degree to which the design could prove to be potentially successful. The representation of the DPEM in the virtual world allows for the evaluation of alternative design configurations before the actual systems engineering life-cycle process is originated. However, the implementation of this approach pre-supposes a structural understanding of the production process(es) that includes physical transformations, information flows and decision rules. This constitutes an effort that is more in line with the definition of engineering production functions carried out in the late ninety seventies (Eide, 1979).

However, there is a question of level of effort associated with this proposed approach. The definition of inputs and outputs for a production enterprise is somewhat straight forward in the context of efficiency analysis. Finding the equivalent input/output representation in a causal system dynamics context is a challenge (Glenn, Schwandt and Triantis, 2007) complicated with the necessity of defining structural relationships in order to quantitatively compute dynamic efficiency performance. The data and information requirements are more demanding and the validation and verification issues (Sterman, 2000) more complex. Nevertheless, there are benefits associated with this modeling approach. It changes the ex-post orientation of efficiency analysis to an ex-ante orientation assuming that the structural relationships remain relatively constant over the time horizon of the study. This leads to a different type of policy analysis where the decision maker can not only compute dynamic efficiency scores but also evaluate the effectiveness of investment alternatives in a virtual world before making investments in the real world.

More importantly the proposed framework creates an opportunity to revisit the various perspectives of dynamic efficiency along with their corresponding axiomatic foundations in conjunction with the variables that are being optimized along with the associated behavioral assumptions. The second implementation demonstrated that the dynamic productive efficiency model could be extended to an example with no pre-determined production function is estimated. The system's production function becomes self-evident as the rates for the model are created through causal relationships. The causal relationships within the model provide a 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. One can also conclude from the implementations, that the dynamic productive efficiency model could be generalized to other efficiency perspectives (for example, partial efficiency considerations) that involve a transient period. Furthermore, there are no known constraints that would prevent the model from having a large number of hill-climbing optimization structures.

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 anticipate 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 to a System Dynamics model with the hill-climbing optimization structure, the desired conditions are found unless a global optimum is not reached.

Hence, this simulation defines the dynamic production frontier based upon expected future behavior. When comparing the results of different simulation cases, one can extract how much productive efficiency can be achieved by changing operational concepts. 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 in the efficiency literature 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.

There are many other issues that could potentially lead to expanding the current DPEM framework. These include but are not limited to how does one most effectively define the performance goals and or standards that drive the system optimization? The inclusion of alternative optimization objectives such as cost minimization and revenue maximization need to be considered. Further, the inclusion of performance targets and peers within the context of this modeling approach also need to be revisited.

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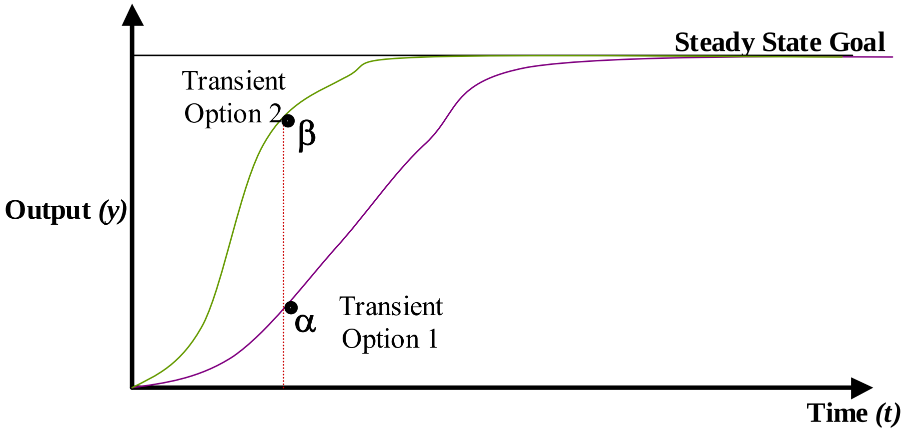

Figure 1: Transient Options

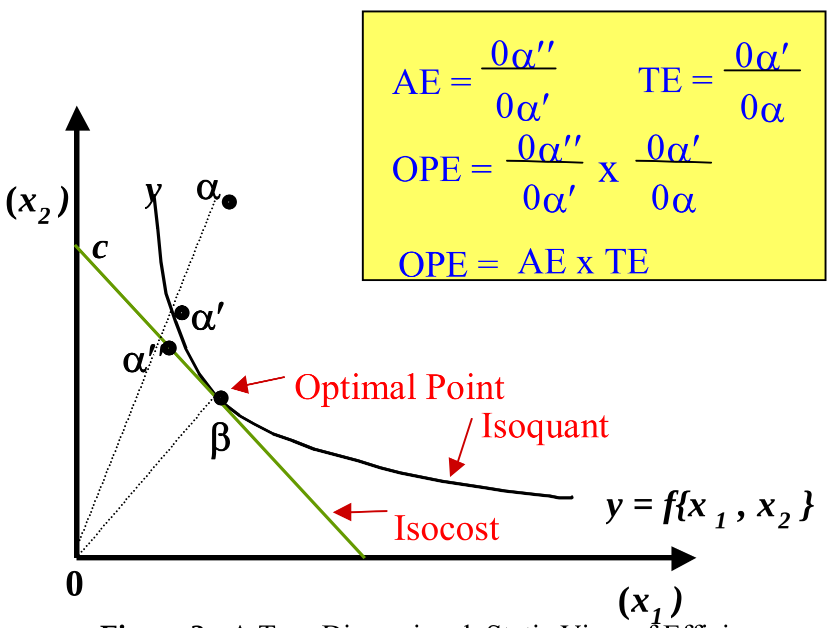

Figure 2: A Two-Dimensional, Static View of Efficiency

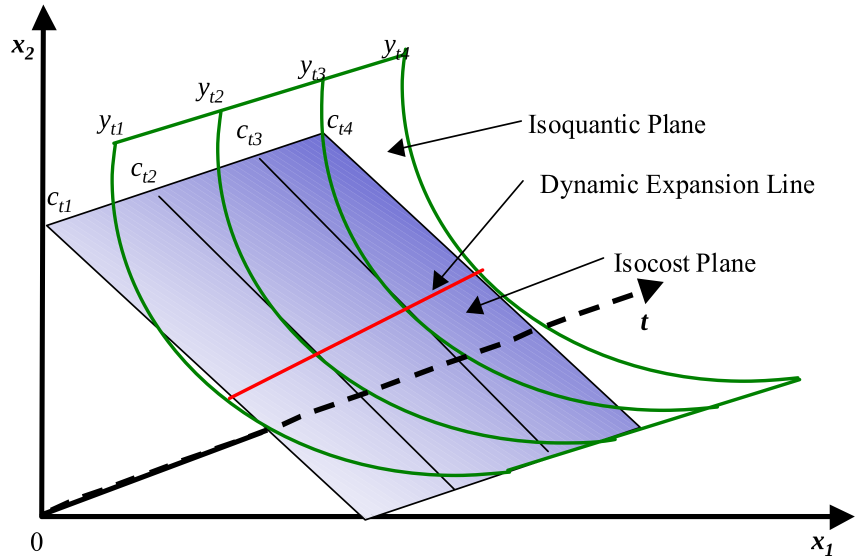

Figure 3: Dynamic Efficiency Expansion

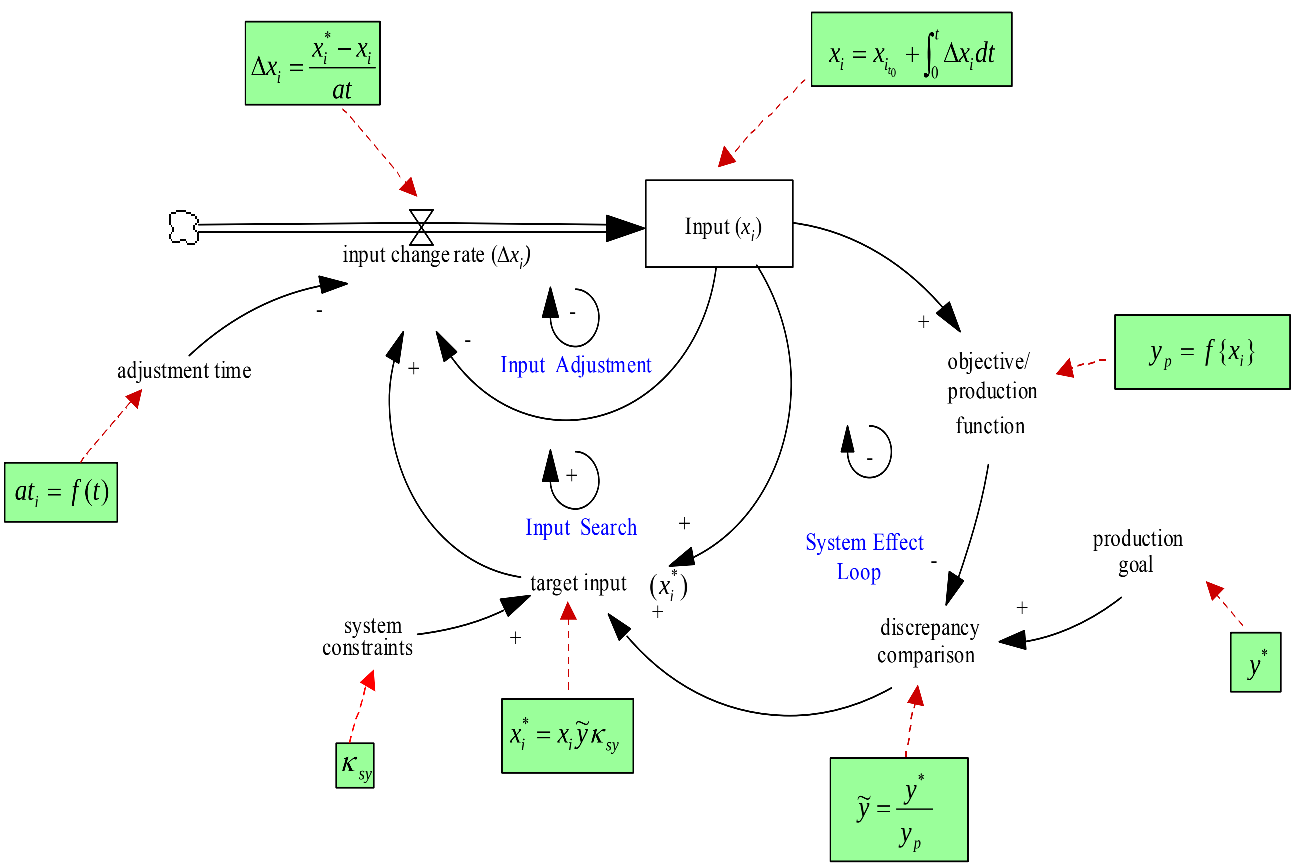

Figure 4: The Generic DPEM (Input-Decreasing Model-Single Output)

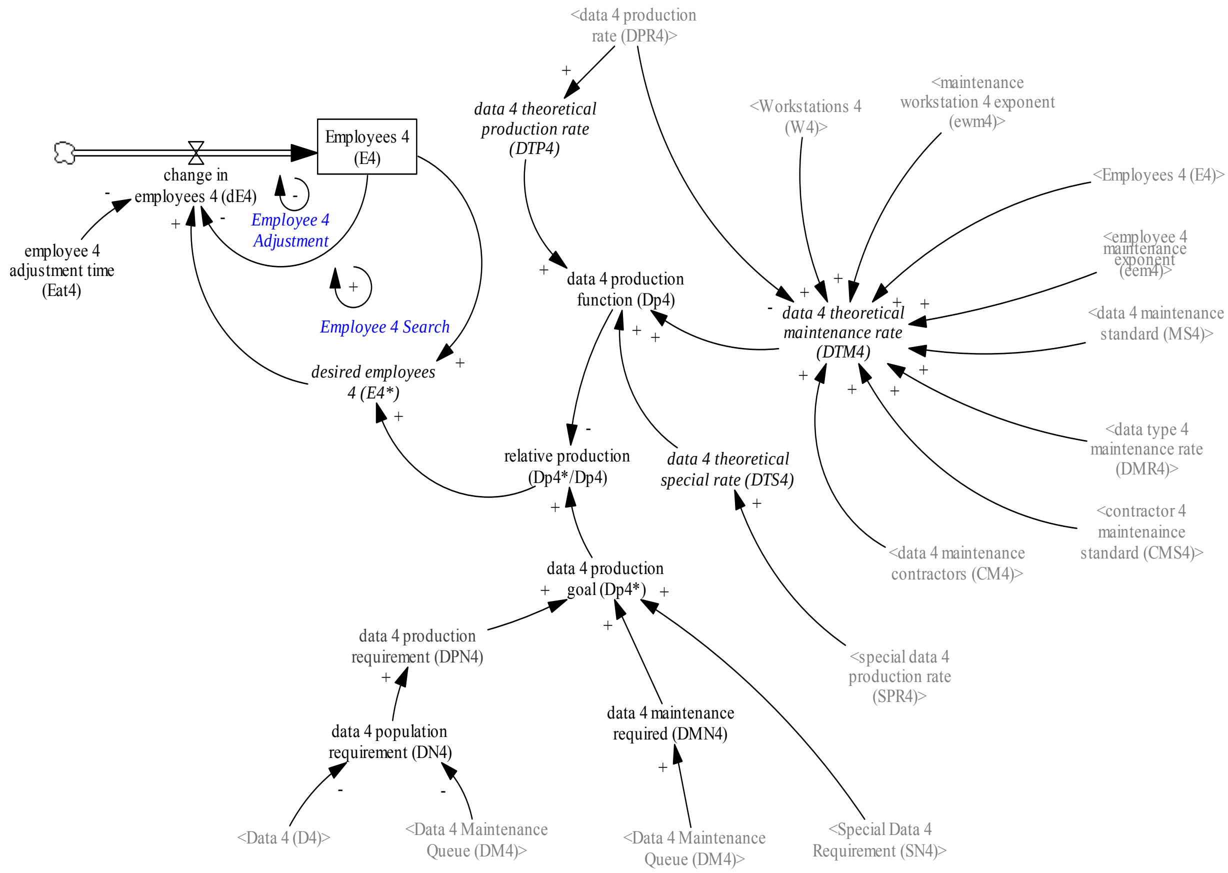

Figure 5: Scenario 4 Employees Hill-Climbing Optimization Structure

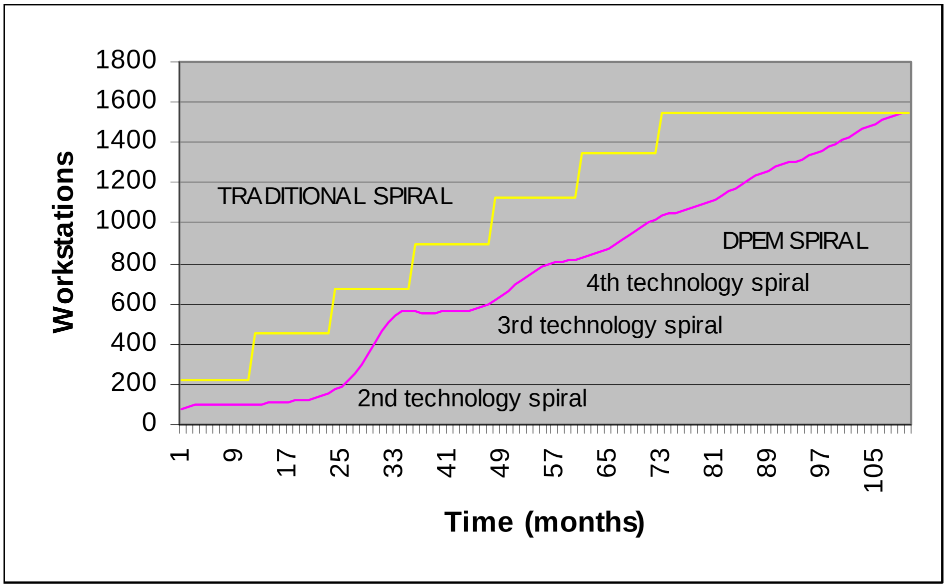

Figure 6: Traditional Implementation Spiral vs. DPEM Implementation Spiral

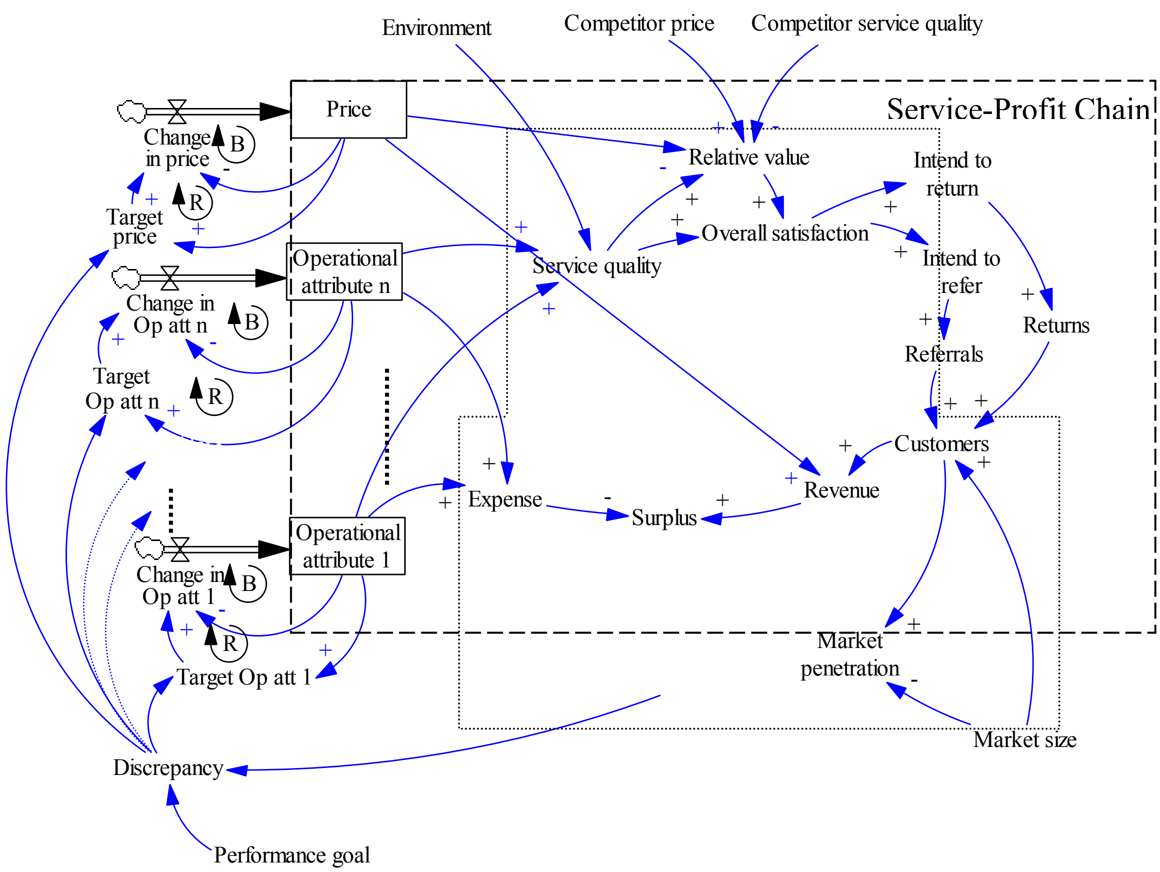

Figure 7: Service Profitability Chain – Operational Model with Evaluation

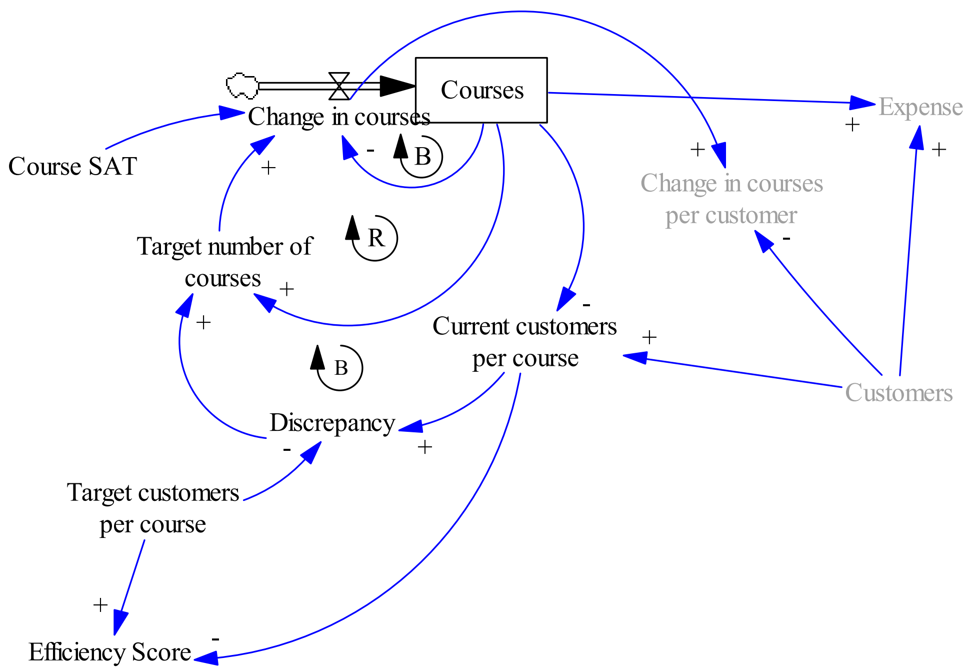

Figure 8: Structure for Computing the Efficiency Score

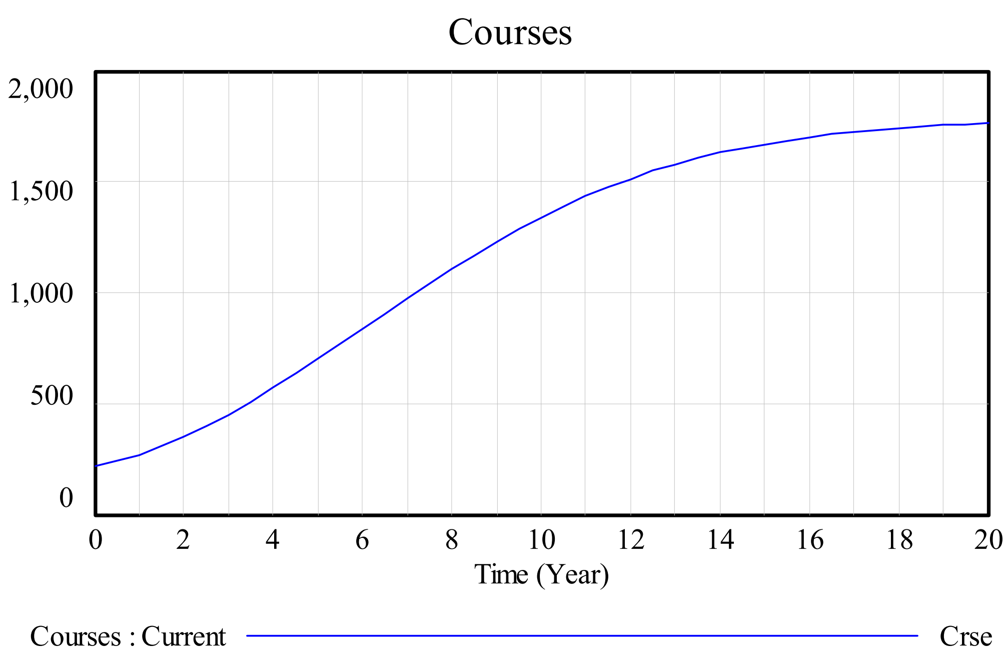

Figure 9: Behavior of the Number of Courses

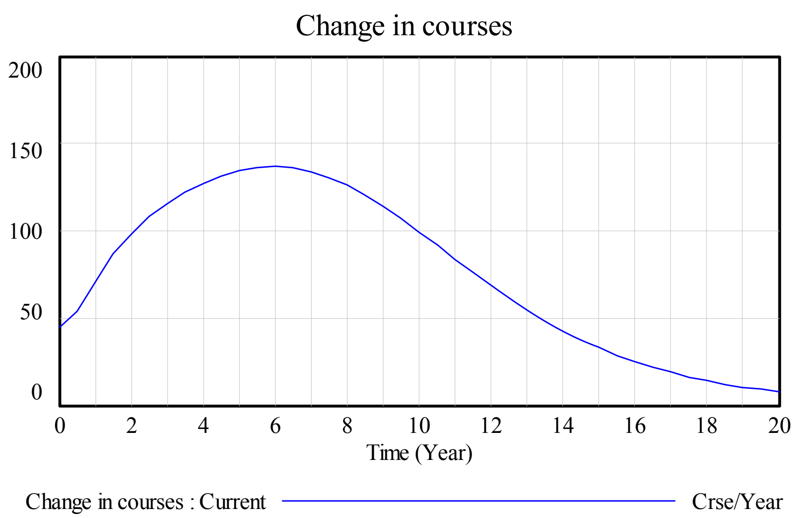

Figure 10: Behavior of the Change in Courses

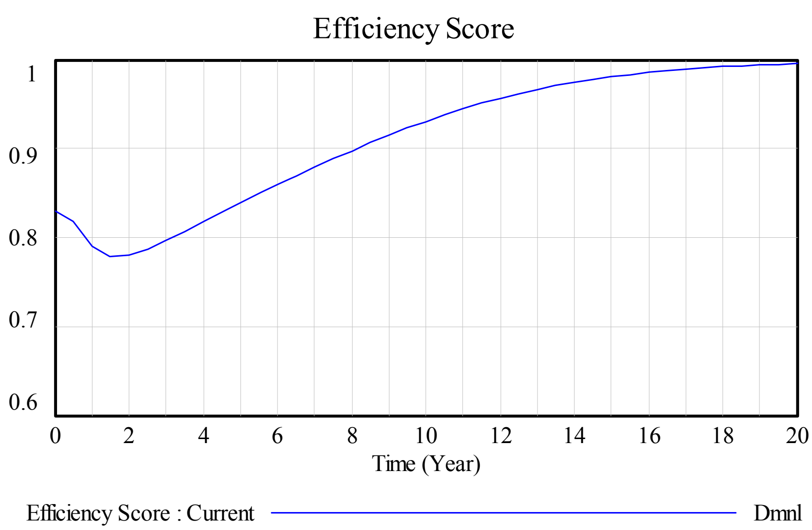

Figure 11: Behavior of the Input Reducing Efficiency Score

Table 1: Steady State values for Key Variables

Variable	Initial value	Final/steady state value
Courses	220 courses	1,765 courses
Change in courses	45 courses	8 courses
Current customers per course	12.05	10.04
Dynamic efficiency	83.02%	99.55%