A Framework for Measuring the Value-Added of Knowledge Processes with Analysis of Process Interactions and Dynamics

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Abstract

In the current business landscape processes are heavily dependent on their use of intangibles and knowledge to produce outputs. This shows the importance that intangible assets have in benefits and value in cases such as project selection which cannot be appropriately managed without considering the role of knowledge. This research develops a framework to measure the value that processes add based on knowledge. It starts by considering current systems and analyzing proposed changes to propose alternative systems in which system dynamics can then be used to model the desired system for behavior measurements. The framework applies knowledge as a way to generate value based on the concept of Kolmogorov complexity. Criteria for project selection is then based on the amount of knowledge measured to generate change. The framework is applied to a case study in a mobile weapon system using unmanned aerial vehicles (UAV).

Keywords
Kolmogorov Complexity, Knowledge Value-Added, Return on Knowledge, Matrix of Change, System Dynamics

1. Introduction

Corporations have traditionally measured success in terms of tangible assets. In highly technical and information-based businesses, the value generated by company processes cannot be measured using cost accounting, which accumulates costs and quantitative data for the purpose of profit measurement. Investments can produce value through improvement or creation of business processes (to increase efficiency) and through improvement of management decisions by speedier and more accurate decision making (which makes them dynamic). Firms can therefore attain value from knowledge-based processes but may not be able to account or measure all or some part of that value. Capital budgeting models can measure the value of capital investments but they rely on measures of cash flows. While tangible benefits can be assigned cash values, intangible benefits providing business value cannot be measured under these financial models. When intangibles are not measured the risks and uncertainty associated with these assets is overlooked. An important question then becomes where and how can the value of knowledge be measured and reported, within accounting models or as totally separate metrics (Guthrie 2001). Another problem is the difficulty of quantifying intangibles when they are not measured to begin with. Employee knowledge, training requirements, and learning curves are some examples of the very important intangibles a manager can use for better decision making if the information is available. Knowledge input is necessary in any business process and the value of knowledge applied to business processes can be used as a measure of value added to the business. Therefore since traditional methods for measuring return on investments or value added are no longer applicable for current knowledge-based business models, the value earned by executing such processes is better measured by accounting for value from knowledge rather than mere monetary tangibles (Pavlou et al., 2005).

With an established need in the current technical- and technologically-based business landscape to account for the impact of intangible assets and the importance of measuring the impact of processes by knowledge management, different methodologies have emerged to quantify the effects of intangibles and knowledge. Some methods identify knowledge as some remainder after tangible capital has been accounted for while others use subjective means and assumptions. But the reason processes are executed is to bring about changes to generate an output. In the case of knowledge processes, how much change takes place on inputs by using knowledge can be considered the most important aspect when executing these processes. And the amount of change to an input by the use of knowledge can be measured by how much knowledge is used to make the change. This last statement is based on both thermodynamic entropy and Kolmogorov complexity, and can be summarized as follows: the required energy or complexity to generate or describe a process output is a measure of change. The measurement of value added from knowledge processes can be accomplished using complexity as the basis for value when executing processes that convert inputs into outputs. Different from measuring value from tangible cost and cash earnings, valuation of knowledge based on Kolmogorov complexity principles can be used to calculate return from investments.

The application of knowledge valuation in this research will focus on measuring the returns on investment and comparing the obtained metrics for decision making. The development of a framework that takes into consideration more than just valuation metrics can greatly increase process selection and decision making. This investigation will propose that considering process interactions and complements as well as dynamic behavior of systems provides a significant improvement to decision making that is based on value added from knowledge. The focus of the research will be the development of a framework for process analysis and decision making. Different from previous studies, the investigation will present a structured approach to analyzing and measuring value based on process complexity along with process interactions and dynamic behavior. Previous work has shown the appeal for measuring knowledge as a way to productivity improvement, but knowledge-based processes also interact in dynamic system structures. Reaching a consensus on why, what, and how the dynamic nature of systems affect the measurements of value-added from knowledge processes becomes a new research area. This research will propose to answer the question: Can knowledge provide better measures of value-added from processes for decision making when aided with process selection and dynamic modeling to provide higher returns on investment?

With knowledge management as a necessary aspect of organizational decision making, a method to measure value-added from knowledge must then measure how much change a process has when generating outputs as follows: the more knowledge used the more change that can take place, and the more value that is generated. With a method for measuring the value added from knowledge as described, what other aspects must be considered for a framework to provide a structured and systematic method for alternative decision making? When alternatives are available, how can one determine how changes or added alternatives would function together in a system? Moreover, what behaviors may take place and how can we know if selected alternatives will affect system stability?

2. Framework

2.1. Framework Overview and Description

The goal of the research is to combine methodologies in an ordered framework that analyzes value-added based on decision on modifying the processes or selecting alternative processes starts with the assumption that the processes are knowledge-based and their complexity determines how much value they add as derived from Kolmogorov-complexity. With the processes' value defined from the knowledge they require to produce their expected outputs, knowledge value metrics can be obtained for both current and proposed processes. The decision on the resulting system of processes is the outcome of an analysis on how the processes function together and complement each other as a system. The goals are to identify how critical process are (more than merely adding more value), how they interact (do they reinforce or interfere in the system?), how difficult they are to implement, and how do stakeholders feel about them. An alternative system would now being analyzed not just by the main driver - value added from intangibles - but by applying methods to determine if they should be considered at all. Since the processes are expected to interact over periods of execution, analysis of system stability and dynamic behavior after implementation will follow by modeling proposed systems. Since these proposed system processes have never been executed, modeling would enable the identification of behavior patterns as a way to test the process changes by studying before implementation. This determines how the processes behave based on the interactions between them over time periods in order to further analyze the actions taken for effectiveness, with the capability of testing the process changes to affect behavior based on metrics of value-added

This initial part of the framework will analyze an "as-is" state of value added by the current processes. Proposed processes will also be analyzed for value added before the framework evaluates current versus proposed changes by recognizing complements between the processes' technologies and practices. Since interactions can make it impossible to successfully implement new, complex processes, this analysis has the goal of anticipating complex interrelationships that surround system changes. During this phase of the framework decisions are made taking into account interactions among all components of a proposed system. After complement analysis, the review of results will yield a proposed "to-be" system that the framework will model to understand the behavior over time of this new, complex system. This analysis will be based on the complex systems are governed by both the influences that the processes they are made of have on each other along with the time delays taking place during execution of processes. These complex behaviors impact value added from knowledge processes over time and this phase of the framework will analyze, by modeling, the stability and behavior of the proposed system. Complex behavior modeling becomes a way to discover effects on value added and modification of inputs and processes can be used to study the behavior of a complete system. Figure 1 demonstrates the framework in general terms based on the steps to accomplish process selection based on value added by knowledge.

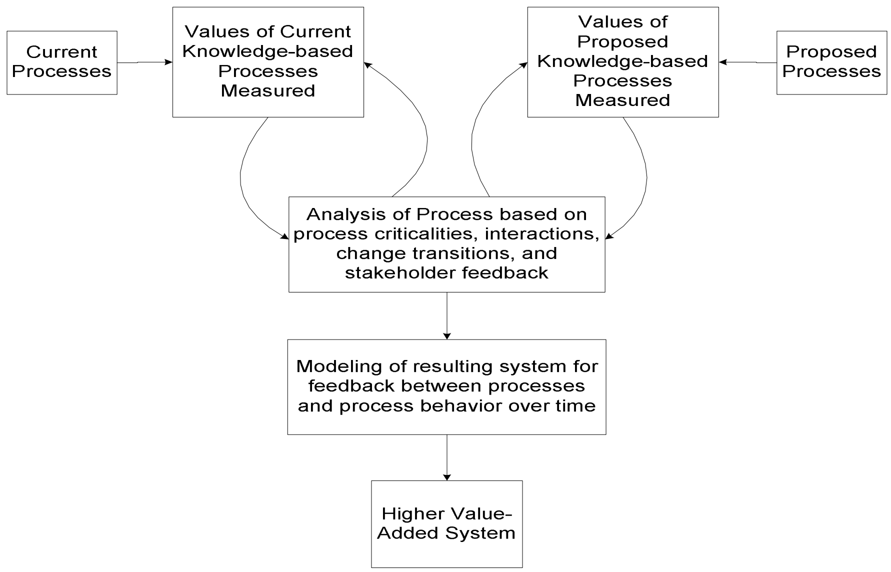

Figure 1: Framework Flow Description

2.2. Analysis of Value Added from Knowledge

Information theory concerns the quantification of information. The most natural approach to define a quantity of information is by viewing it in relation to individual objects instead of in relation to a set of objects (from which the individual objects could be selected). The quantity of information in an object can be defined by the number of bits needed to describe the object, and a description of an object is useful only if the full object can be reconstructed from the description. The processes of information exchange, of communication, transcription and processing are covered under information theory. KVA applies the quantification of knowledge following information theory by using a description of the knowledge needed to execute a process and generate an output (be it by learning time, binary measures, or by quantity of instructions). KVA requires that the outputs are useful as expected, being reconstructed from knowledge that describes how to execute a process. KVA applies the principles of Kolomogorov's Complexity (K-Complexity) Theory, an established and proven framework widely used in the natural sciences to analyze structure creation in systems. It is a universal measure of changes in the form of matter. With this in mind, creation of Kolmogorov complexity (and the equivalent information) can be viewed as the universal activity of people, which includes the creation of value in business processes.

Kolmogorov complexity is rooted in information theory (along with probability theory and the concepts of randomness). While closely related to problems in information theories, K-complexity aims to provide a way to measure ‘information’. KVA bases the concept of change being proportional to and requiring knowledge on K-complexity theory. Under KVA the changes in entropy are the product of processes that apply information. Kolmogorov uses the “bit” as the unit of measurement, one bit typically defined in information theory as the uncertainty of a binary random variable that is 0 or 1 with equal probability, or the information that is gained when the value of such a variable becomes known. KVA essentially defines the input (original or unchanged variable) as variable 0 and the output (a changed variable with value added by information) as variable 1. The amount of information in an object may be interpreted as the length of a description of the object.

Entropy is used by the KVA methodology when KVA is described by changes in structure that can be measured as changes in entropy. Since businesses are complex open systems that exchange information with their environments they are capable via processes to change inputs (i.e., information, materials, etc.) into products. When these change processes take place, value is added. This approach assimilates to the language of thermodynamics, where an input (a) becomes and output (b) via a process (P). The change between an input (a) and an output (b) is dependent on the knowledge needed to execute the process (P). The difference (i.e., change) between the inputs from that of the outputs is the value provided by the people, systems, or processes which acted upon the inputs. The major assumption of KVA is that change, and therefore knowledge, are proportional to value. The output from a process is a function of its input, such that: $P(a)$ = b. A process P acts on input a to produce an output b. If a equals b, then no value was added to the input by the process P. The following assumptions provide a derivation of how valuation works under KVA based on KVA's business application of Complexity Theory:

- if a = b, no value has been added, therefore
- value can be added only through changes to input, and
- "changes" can be described, therefore
- the minimum number of changes is equal to the length of the shortest description, so
- "value-added" = "number of changes" = "length of the shortest description"

With the relationship between entropy and change, KVA addresses value-added with the assumption that if a business process P is such that no change takes place (output is equal to input) then no value is added by the process. KVA also infers that the value-added by a process can be proportionally associated with the change in entropy. A parallel between transformation of information in information theory and transformation of substances in thermodynamic is made to define entropy as it relates to information processing. In thermodynamics, the difference in entropies is proportional to the amount of thermodynamic work needed for the change, say when a substance is changed from a state a to a state b, such that:

$$\Delta E = E(b) - E(a)$$

In the equation above the differences in the entropies of a and b is proportional to the amount of change needed to make the change. The parallel with information theory comes in the form of strings (vs. a thermodynamic "substance"). A string is generally defined as a data type which stores data values in some sequence (usually bytes). The elements in a string stand for characters according to some type of encoding. DNA, texts, and spoken languages are examples of naturally occurring "strings". The complexity of a string is the length of the string's shortest description. In the case of information or knowledge processes versus a material or a substance in thermodynamics, an information theory bit is proportionate to a unit of "complexity", and this complexity is the underlying unit that is described as a unit of "knowledge".

If a description of x, $d(x)$, uses the fewest number of characters it is of minimal length or minimal description. The Kolmogorov complexity of x is the length of the number of characters in its description d(x), and is defined as:

$$K(x) = |d(x)|$$

And when there is an amount of "thermodynamic" work or change needed to transform a string x into a string y, the Kolmogorov complexity $K(x)$ is defined as the length of the shortest description of x. When that description of the complexity of x, $K(x)$, is changed by a process, the change or entropy is defined as a change in K-complexity:

$$\Delta K = K(y) - K(x)$$

Where the change in information, or the entropy caused in the string, is the difference between the complexity of input, $K(x)$, and that of the output $K(y)$. The calculation of value added comes from the calculation of entropy or Kolmogorov complexity change that is caused when the process transforms the input into an output. This again recalls the thermodynamics principles.

Entropy is a key measure of information in information theory and is usually expressed by the average number of bits needed for storage or communication. Entropy quantifies the uncertainty involved when encountering a random variable. This means that an event with a higher number of likely outcomes will have more entropy than one with a smaller amount of likely outcomes.

To accomplish the calculation of value-added in business processes based on entropy or K-complexity, a relationship between business change processes and the descriptions (e.g. information strings) of those processes is used. To explain this, assume that a process can be done two different ways: by an original process P or by a modified process M. The original process P has an input a and output b; the modified process M has an input x and an output y. (The M in this example is modified process, which can be thought of as U for a universal computing machine or universal Turing machine)

Subsequently, if:

1) We map a to x in a one-to-one relationship such that a is a set of all inputs possible to process P and x is the set of all possible inputs to process M, <u>and</u>
2) We also map b to y in a one-to-one relationship such that b is a set of all outputs possible from process P and y is the set of all possible outputs from process M, <u>then</u>
3) $M(x) = y$ if and only if $P(a) = b$

In the above, the M representing the modified process can be a computerized or information technology process, using a computer program or software code which represents the process and can be viewed as a description of the process outputs. The changes brought about by a computer program in a computer are a reflection of the changes. This is because the K-complexity in the program, as would a string, reflects the structure changes in the inputs from a value-adding process.

To understand how Knowledge Value Added is applied for knowledge processes in the same fashion as the ideas of entropy and K-complexity, we recall the concept of inputs thru processes to generate outputs. KVA is based on the concept that in a process where change takes place there is always knowledge used to change the input and generate the output. The change made to an input is the value added to that input via the change process. The assumptions of KVA include the reasoning that the value created by a process is relative to the change that the process affects on the input and that change can be measured by the quantity of knowledge needed to generate change. Knowledge can be defined by:

1) How much time it takes to acquire the knowledge (or learn how) to execute a process.
2) The amount of process instructions required to produce an output (Such as the number of process description words, pages in a manual, and/or lines of code pertaining to each sub-process.
3) Creating a set of binary yes/no questions so that possible outputs are represented as a sequence of yes/no answers, to calculate the length of sequence of yes/no answers for sub-processes. This is known as the Binary Query approach of KVA.

When KVA describes the amount of change in terms of the time needed to learn a process, these units of learning time are proportional to an information bit, which is proportional to a unit of K-complexity, which in turn is proportional to a unit of change. Change in KVA theory can be described in any form as long common units are used. Hence, learning time, process description, or binary query can all be used as descriptive languages for change measurement under common units of output.

The KVA methodology is then based on the concepts of complexity theory and was developed based on the concept of units of change or "units of complexity". The information "bit" was the best theoretical way to describe a unit of Kolmogorov complexity and therefore the knowledge-based concept describes change in terms of knowledge required to make the change. KVA aims to provide a measurement of the knowledge needed to produce outputs (by changing inputs). The underlying assumptions are as follows: humans or technology change inputs to outputs thru processes, and by describing process outputs via knowledge as the common units required to produce outputs, revenue can be assigned along with cost.

With bits used to describe units of complexity, the "knowledge metaphor" of KVA defines change based on the amount of knowledge needed to make changes under intangible activities. KVA looks to standardize the outputs of knowledge processes in terms of the units of complexity or change required to produce outputs. These outputs have value that is derived from the knowledge needed to change the characteristics of the inputs. Value under KVA is an assumption of the changes that knowledge brings about when generating an output. The value added by a knowledge process is proportional to the amount of knowledge required to execute the process. As value is measured based on the knowledge to create outputs, return on investment, or under KVA return on process (ROP), is calculated applying value and cost. ROP is what KVA calls its measure of value creation for processes with a predetermined output. ROP is basically a return on investment *in process*. The derivation of ROP under KVA is as follows: the internal performance V of a process is defined as

$$V = I / C$$

Where I is the amount of information or K-complexity to execute a process and C is the cost to produce the specific amount of K-complexity needed for the process (while this explanation talks about a single process, the performance of compounded processes can also be defined by using weighted averages of component performances). To go along with performance V, a relation to an external measure of performance or value is needed to account for the value added by I (as information, knowledge or complexity). This relates to return on investment (ROI), where the price of an output accounts for the money gained (or lost) and is the numerator in a ratio against the cost to execute. For example, when a business obtains a monetary value from a process output, that value correlates to the complexity of the process that generated the output. This can also be seen when a customer pays for an output when a client pays a set price for a unit of information no matter how it is produced. KVA derives return on knowledge (ROK) as the ratio of the value that the complexity or knowledge of a process generates and the cost of the process. Return on Knowledge (ROK) is the ratio of revenue allocated to a core area when compared to its corresponding costs. With knowledge as a surrogate for common unit outputs, ROK determines knowledge value to cost ratio for processes.

2.3. Change Analysis

Management of change, based on the importance of interconnections and considering that system optimization requires cohesive processes, can be accomplished using the Matrix of Change (MOC). Drawing from Quality Function Deployment (QFD), the proactive definition of activities needed to meet requirements "permits quality and customer needs to be designed into the product, not added on." (Richardson 1997). QFD applies mechanisms that analyze relationships and correlations by which requirements are translated to be successfully using a matrix called the "House of Quality", by applying values and priorities to the relationships between needs and requirements. Effective management of change also requires recognition of the critical role of interactions which "can make it impossible to successfully implement a new, complex system in a decentralized fashion. Instead, managers must plan a strategy that takes into account and coordinates the interactions among all the components of a business system." (Brynjolfsson 1997). QFD has proven successful in change management by early evaluation of requirements and expectations. The proposed framework can relate this idea when it shows a need or a "what" (value added from knowledge) with a "how" (process changes).

MOC provides effective change management as it recognizes complements between technology, strategy, and practice by anticipating complex relationships that come about from change. MOC considers the issues of stability under new changes, sequence of processes, pace of change, implementation in new or available locations, and the sources of value added from the interests of stakeholders. The analysis is accomplished in four steps: three matrices (current practices, desired practices, and transitional state bringing current and desired together) and evaluations by stakeholders to identify the importance of processes to activities by the stakeholders. The first of the four MOC steps is to identify critical processes and practices that are broken down into "constituent parts" or the processes expected to meet or improve practices or goals. The second step classifies system interactions by matrices that identify processes as ones that increase returns on processes they complement (reinforcing) or ones that decrease returns on processes it competes against (competing). A grid based on QFD's "House of Quality" starts in this step in the way of triangular matrices: a horizontal for existing processes and a vertical for proposed processes. These "interference matrices" use grid signs at the process junction locations: plus signs (+) for reinforcing, minus (-) for competing, and no sign for weak or no interactions. The plus and minus signs can be determined in different ways as many times it can be self-evident but other formal theories can be used as well as empirical methods and surveying of personnel. Step three identifies interactions of transitioning by implementing proposed processes by combining the horizontal and vertical matrices from step two into a matrix to determine interactions between existing and target practices using the plus and minus signs configuration previously applied. The fourth step surveys stakeholders on how they perceive current and target processes in terms of building a better system, output, or value-added. Those surveyed will use a five-point Likert scale as follows to rate each process:

- +2: Extremely important practice/process
- +1: Important, but no essential practice/process
- 0: Indifference
- -1: Some but not essential desire to change or reject a practice/process
- -2: Strong desire to change or reject a practice/process

Figure 2 demonstrates completed MOC steps one and two (left) and three and four (on the right).

The measure of business value evaluated from stakeholder's perspective for the purposes of this framework will apply the quantifiable units of knowledge value-added as the basis for this step of the MOC. It answers the MOC question: what are the greatest sources of value? The change process has a higher chance of success by the identification of complementary structures and analysis of interactions between processes provides the most important tool for decision making without the significant commitments which change would otherwise incur. Such analysis also provides a smooth transition into the next phase of the framework that will model the proposed systems for behavior and stability during process executions over time.

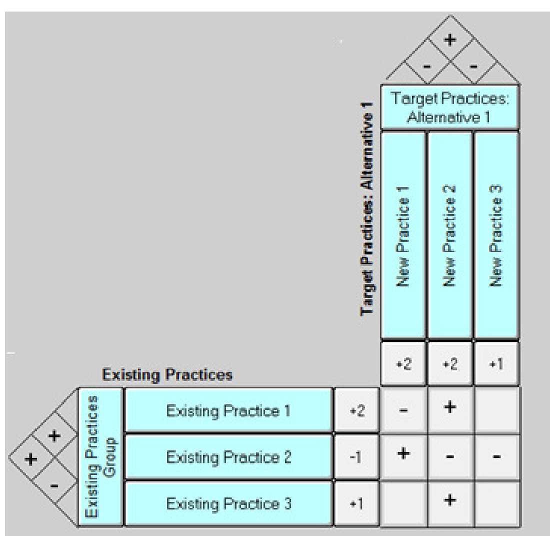

Figure 2: MOC System and Transition Interactions

2.4. Dynamic Modeling Application

The systems resulting after MOC analysis in this research can be made up different combinations including processes that have never been executed before and/or processes previously executed within other systems. The dynamic complexity of knowledge-based processes makes it difficult for managers to make decisions based on the behavior of these processes. Like most processes, knowledge-based processes exhibit non-linearity that can make decision making difficult because a simple change can produce complicated effects. These complexities imply a need to understand the interactions that taking place in knowledge-based systems. A behavioral view of system dynamics can focus on system (and process) characteristics that may “make or break” the complete system. A behavioral model can provide reproduction of dynamic systems before any change commitments. The implementation of changes then becomes a product from the insights gained during the dynamic simulation modeling. The basis for modeling the behavior of process that make up a complex system is the recognition that system structures are as important as the individual processes, while there are properties of a complete system that cannot be explained or even recognized by the behavior of individual processes. This research will analyze the behavior of proposed processes functioning as a whole new system. With a proposed system composed of processes generated from the first two major phases of the framework, this last phase will model the system for behavior over time to understand complex issues and problems that arise from dynamic behaviors.

The System Dynamics (SD) approach is unique in its study of the feedback and stock-and-flow dynamics to display what could be severe non-linearity in systems that may appear simple. SD uses visual representations of the information feedback and circular causality that conceptualize the structure of complex systems, in turn communicating model-based insights (Sterman 2000). Feedback loops are present when information from an action (e.g. a knowledge process) moves through a system and can influence the system’s behavior. System dynamics modeling as the last phase of the framework will analyze the dynamic behavior of alternative systems. The modeling of alternatives would simulate processes as continuous steps in a system that begins with an input and finishes with an output. SD modeling would be used to influence inputs, value-added, and cost metrics. Figure 3 summarizes the methodologies used in terms of the tasks that the framework looks to accomplish. The outputs of the SD model will help analyze the behavior and success of alternative knowledge systems over time by providing KVA metrics.

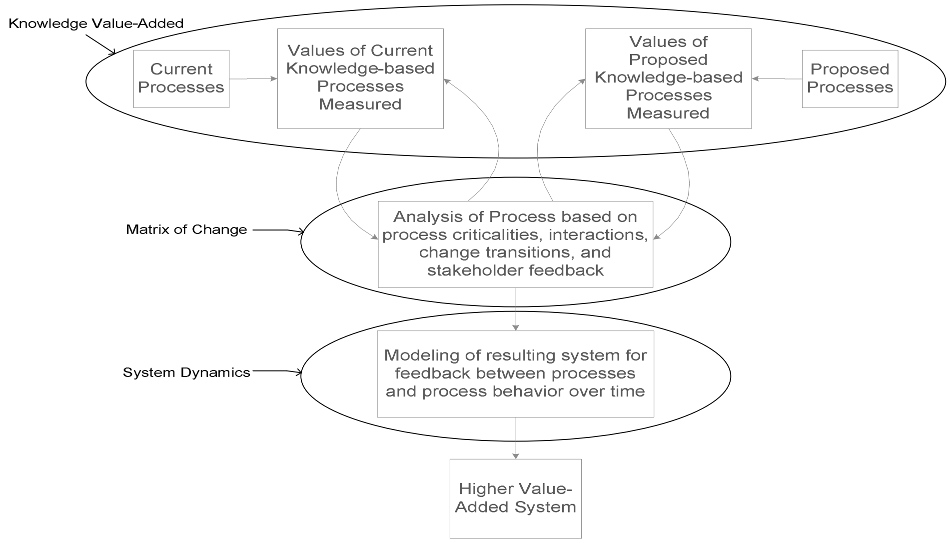

Figure 3: Methodologies to accomplish the Framework's objectives

3. Case Study

3.1. Case Study Introduction

A previous study on Department of Defense (DoD) acquisition programs looked to improve the use of benefits in analysis of alternatives (AoA) by making a system dynamics model of a military operation and integrating it with KVA in order to improve the accuracy of KVA estimates in AoA processes. The main problem identified by the research was measuring the benefits of material alternatives. AoA became difficult due to alternative diversity, metric selection and performance measurement among other factors. Along with cost estimates pre-dominating the AoA, the research arose from the difficulty of incorporating benefits from materiel since many important benefits were intangible in nature. The goal of the research was to include benefits in AoA in terms of common units, to enable better comparisons among alternatives based on value instead of merely cost. When a materiel solution is needed, AoA is used to meet criteria and reach decisions. When needs are derived in an area that can only be met by new materiel, AoA helps comparison of options (for example manned or unmanned aircraft vs a missile, chemical vs kinetic energy kill mechanisms, etc.). After lessons learned on a Javelin anti-tank weapon system concept which had three missile technology alternatives to award a development contract and where the chosen alternative was selected based on a capability not a stated requirement that provided value. While there were lessons on requirements, bureaucracy, and technology readiness, analyzing alternatives under a single undefined and qualitative factor of performance (gunner survivability) ultimately drove the chosen alternative. A parameter which promised the most of what was impossible to quantify became the main factor when selecting alternatives and the process failed in reaching a final solution faster and more directly due to insufficient articulation of benefits in the AoA process. The Javelin program showed a need for common units of benefit estimates in AoA, leading to inclusion of units of benefit along with cost.

3.2. Case Study Problem Description

Weapon acquisition programs typically conduct AoA to select material solutions based on viability and costs to make decisions regarding further development and production. Concepts are then analyzed as part of a material solutions analysis by which various cost estimates are generated from cost comparisons. The emphasis on costs in the early stages of acquisition should not become the main (and even less only) criteria for alternative selection. This practice caused a feeling of disparity between costs and benefits from effective operations. The main problem area stated by the Naval Postgraduate School (NPS) research looked to improve was the estimation of benefits, but more importantly in common units. The main problem stated by the previous research was the difficulty of defining common metrics to measure performance in order to account for benefits from alternatives. This measurement of benefits using KVA was integrated with dynamic modeling of a weapon system for unmanned aerial vehicles (UAV) to make decisions on upgrading the system. The modeling uncovered synergies between the UAV weapon system processes which (while being measured using common units) increased the amount of alternatives to analyze. The research concluded that this measurement of benefits along with modeling of the dynamics of the system's alternatives was a major improvement from decisions made using costs of alternatives (Housel and Cook 2005; Housel and Bell 2001; Housel et al. 2001).

The case study being proposed in this paper will look to benchmark the findings from the NPS research and more importantly improve on decision making by integration of common measurement of benefits from intangibles (included research but done after dynamic modeling), alternative decision making based interactions and complementarities between alternatives (not included in original research), and dynamic modeling to analyzed changes in benefit values after a new system has been defined (modeling used in previous research, but before any complexity/benefit metrics were calculated). The NPS proposed as an item for further investigation the ability to indicate the sub-processes that improve the alternatives. As an example, while it was thought that increasing the "fuel capacity" alternative was the reason a sub-process called "fire mission development" was improved, it was discovered from the modeling that the actual cause for the improvement was an increase in "vehicle range" because this alternative reduced the chance of losing a target if it was missed (versus not being able to re-acquire a missed target and needing more time, fuel use, etc.). This will be researched under the alternative decision making phase of the framework, which will provide a method to identify if changes are to be implemented. The NPS study also made use of modeling to generate forecasts of performance during acquisition, "comparing those forecasts with actual operations, and using the results to improve the model fidelity with the system. The improved model can then be used to analyze proposed changes or replacement of the system throughout its lifecycle" (Ford, Housel and Dillard, 2010).

3.3. Matrix of Change

Under the NPS research a new version of the Predator UAV was being developed to enable it to engage opposing UAVs. Only one improvement alternative was to be selected from three options which stakeholders value differently: payload, dash speed, and range. The study's analysis focused on value compared to cost in terms of the capabilities of the systems. KVA was integrated with SD to investigate how modeling weapon systems can improve the accuracy of KVA ratios. Assuming a new version of the predator UAV is being developed to engage enemy

UAVs. This will increase the fraction of targets missed because UAVs are faster, more agile (than land targets). There is access to only some limited resources to improve performance. Stakeholders value payload, dash speed and range differently and want recommendations on different improvements to select only one of the improvements. Examples of some of the alternatives for improvement were:

- Increase size of power plant: can increase the vehicle's payload, dash speed, or combination of both; requires an increase in fuel capacity to not reduce range.
- Redesign transmission: will increase dash speed.
- Increase fuel tank size: will increase range but decrease dash speed unless power plant increased.
- Reduce time required at base between trips to station: increases time the vehicle is on station and available for missions.

The operation of the system with each potential alternative was simulated to calculate KVA productivity ratios for subprocesses and for the whole system (the three subprocesses that are impacted by the characteristics of the vehicle). Referencing the following table, the AoA suggests that the increasing of fuel capacity 100% is the alternative that improves the system the most. If there are inadequate resources to implement this alternative fully, then increasing fuel by 50% can be attempted (since it will still bring the highest improvement). The ones that do not improve performance (last three with negative change from base case) can be eliminated from consideration.

Table **1** summarizes the results.

This research proposes a MOC analysis before system dynamics modeling (as where the NPS research performed SD in the beginning) where the alternatives are analyzed against available practices or goals. For the NPS study this proposed framework will perform an MOC analysis on the alternative practices against the system sub-processes. MOC will analyze the practices of increased power plant size, increase fuel capacity, redesign transmission and reduce time at base against fire mission development, weapons movement, and engaging targets. The stakeholders being interested in payload, dash speed, and range will influence their view of target practices differently.

Table 1: Predator Upgrade Alternatives Results

		Sub-process KVA ratios			Weapon System	
		Develop Fire Mission	Move Weapons	Engage targets	KVA ratio	% Change from Base Case
	Predator Base Case	943	50	5,094	705	0.00%
Improvement Alternatives	Increase fuel capacity 100%	**1,886**	50	5,094	**951**	34.90%
	Increase fuel capacity 50%	1,415	50	5,094	831	17.90%
	Increase power plant 100% for payload	849	50	7,641	771	9.40%
	Increase power plant 50% for payload	849	50	7,641	771	9.40%
	Redesign transmission for 100% faster dash speed	943	**100**	**10,188**	741	5.10%
	Redesign transmission for 50% faster dash speed	943	75	7,641	727	3.10%
	Increase power plant 100% for dash speed	849	**100**	**10,188**	717	1.70%
	Increase power plant 50% for dash speed	849	75	7,641	702	-0.40%
	Reduce time at base 50%	943	52	5,094	699	-0.90%

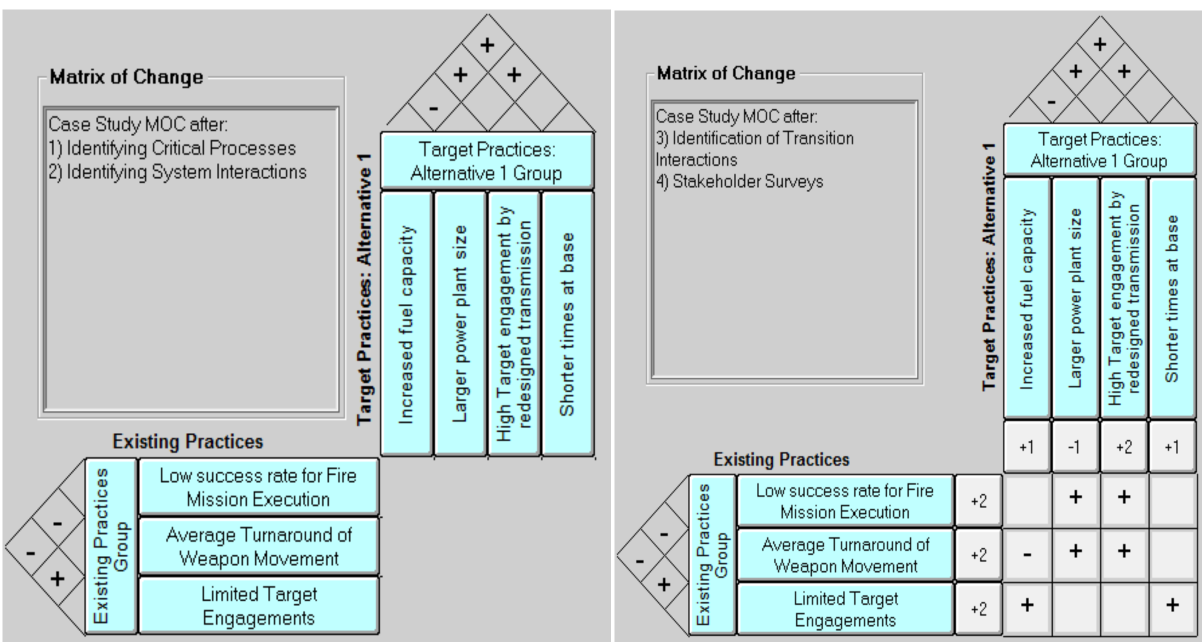

Figure 4: MOC for NPS Study

The MOC analysis shown in Figure 4 provides insights into complementarities of practices (and assets) by the interaction signs in the matrix. Increased fuel capacity and shorter times at base are practices with two reinforcing interactions and which reinforce each other, while larger plant and redesign transmission only have one reinforcing relationship each. The questions of feasibility, sequence of execution, location, pace/nature of change, and stakeholder evaluations offer guidelines on how, when, and where to implement changes. The difficulty of transitioning to the alternative processes is defined by +/- signs in the cross-sections for existing and target processes. This MOC analysis would first eliminate the “reduce time at base” alternative based on its interaction score and negative importance to the process while considering the remaining three, with increased power plant demonstrating the easiest transition and "increase fuel capacity" showing the strongest importance (+2).

3.4. Causal Loop and System Dynamics Model

After decisions on implementing new processes, system dynamics can model the resulting proposed system. CLDs provide "maps showing the causal links among variables with arrows from a cause to an effect" (Sterman 2000) capturing the dynamics of a modeled process and applicable to the capture of hypothesis about dynamics' causes and to demonstrate the feedbacks of a specific process. Stock and flows structures are descriptions of variables with rates or "flows" which can increase or decrease. These flows accumulate into the most important information in a dynamic model as "stocks" which represent system states. An appropriate systems dynamics model for measuring knowledge value requires variables for the state of the system (stocks), for the increase and decrease of these stocks (flows), and variables that can be linked to stocks and flows supporting the description of the model behavior. The resulting system from the selected alternative processes in the MOC analysis is now put into a SD model to the complete system processes of moving weapons and acquiring a target under the NPS study. The modeling of alternatives would simulate processes as continuous steps in a system that begins with an input and finishes with an output. Revenue and cost are used for knowledge valuation based on KVA methods, and make up the stocks for each of the processes (these stocks are considered return on knowledge stocks). System dynamics modeling would be used to influence inputs, value-added, and cost metrics. This modeling allows graphing of stocks of value-added to provide the KVA metrics to be analyzed for results in the framework. Figure 5 demonstrates the CLD of the alternative system from the processes selected in the MOC analysis. This is the final phase of the framework and is to provide, by modeling before implementation, insight on the behavior of the complex dynamics of a knowledge system over time. Figure 6 represents a SD model that would be generated as the final major step in the framework for this case study.

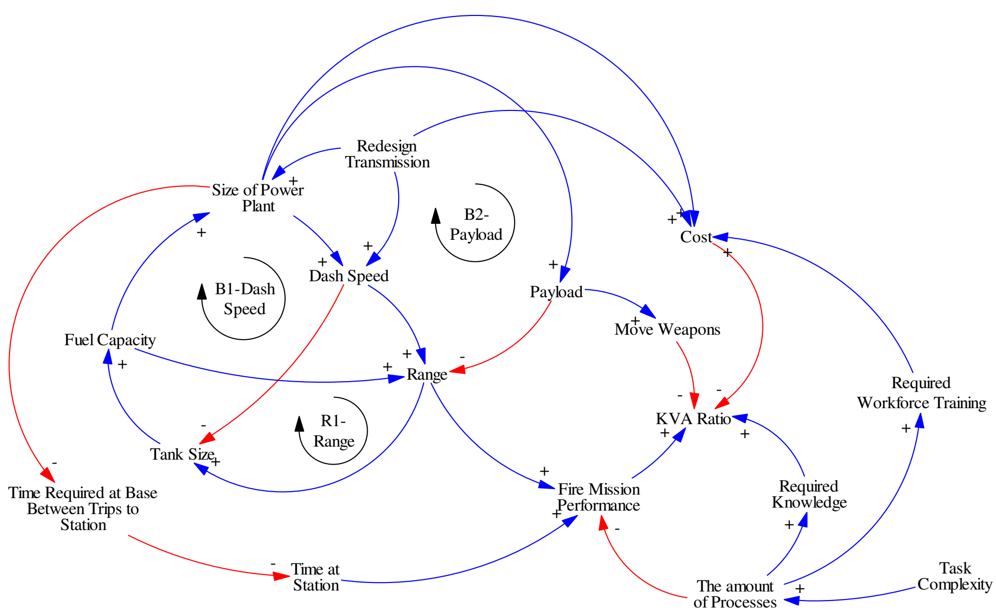

Figure 5: Causal Loop Diagram of UAV Weapons System

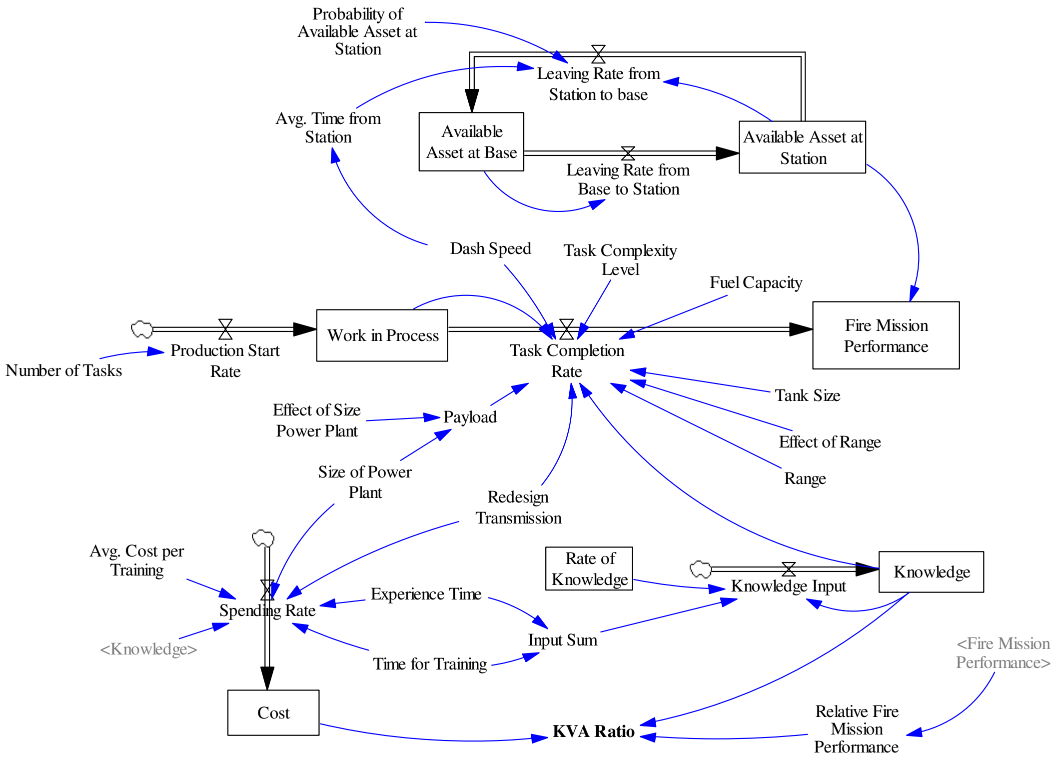

Figure 6: System Dynamics Model of UAV Weapon System

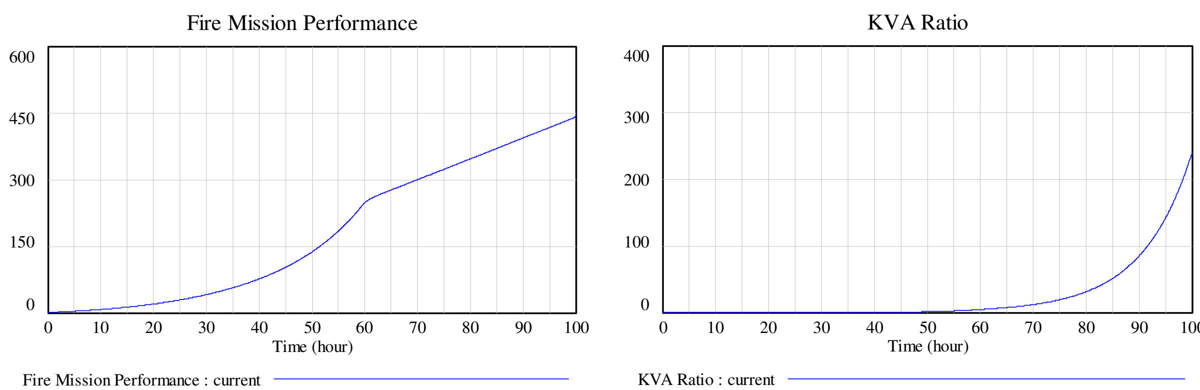

Figure 7: The Results of Fire Mission Performance and KVA Ratio

3.5. Model Optimization

The optimization option that comes with Vensim DSS provides an efficient tool for policy analysis. An efficient Powell hill-climbing algorithm searches for the best set of policy parameter values to maximize the objective function. The Powell hill-climbing algorithm was developed by Powell (1964) and it is an optimization approach that searches the objective in a multidimensional space by repeatedly using single dimensional optimization. The method finds an optimum in one search direction before moving to a perpendicular direction in order to find an improvement (Press et al., 1992). The main advantage of this algorithm lies in not requiring the calculation of derivatives to find an unconstraint minimum of a function of several variables (Powell 1964).

With the purpose of reducing the current level of Work in Process inventory (see Figure 8), we apply policy optimization to the parameters that affect the Task Completion Rate (see Table 2). This rate initially starts increasing until it reaches a peak and then stabilizes. The objective will be to maximize the Fire Mission Performance while reducing the Work in Process inventory.

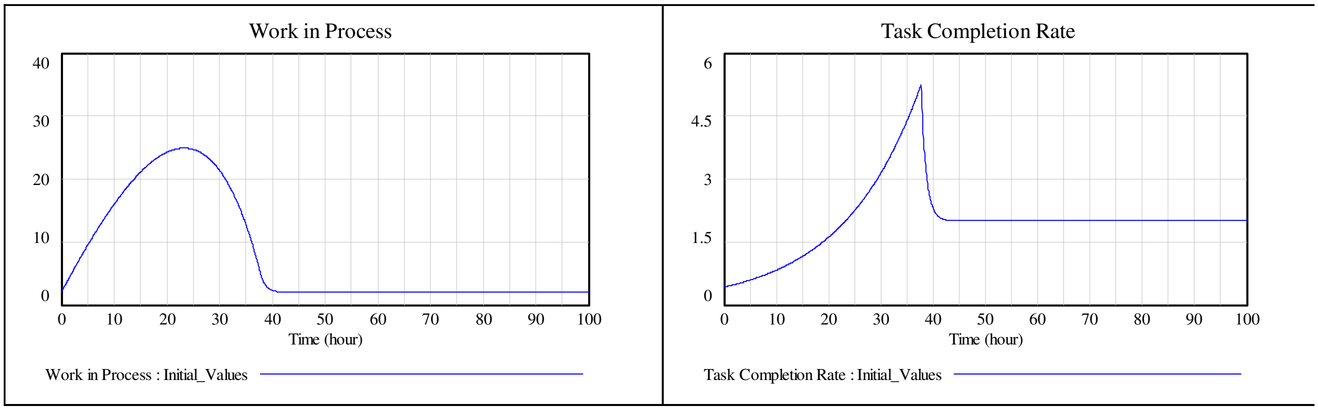

Figure 8: Work in Process inventory and Task Completion Rate before optimization

Table 2: Comparison of new parameter values with the original values

	New values from the optimization	**Original values of the model**
Fuel Capacity	2.06	1
Tank Size	1	1
Redesign Transmission	1	1
Size of Power Plant	1	1
Effect of Range	0.85	0.85
Effect of Size of Power Plant	1	1
Task Complexity Level	4	4
Range	2	2
Dash Speed	1	1

From Table 2 and Figure 9 we can conclude that although the Fire Mission Performance remains almost the same, increasing the Fuel Capacity it is possible to the reduce and stabilize the Work in Process inventory. The other parameters remain unchanged.

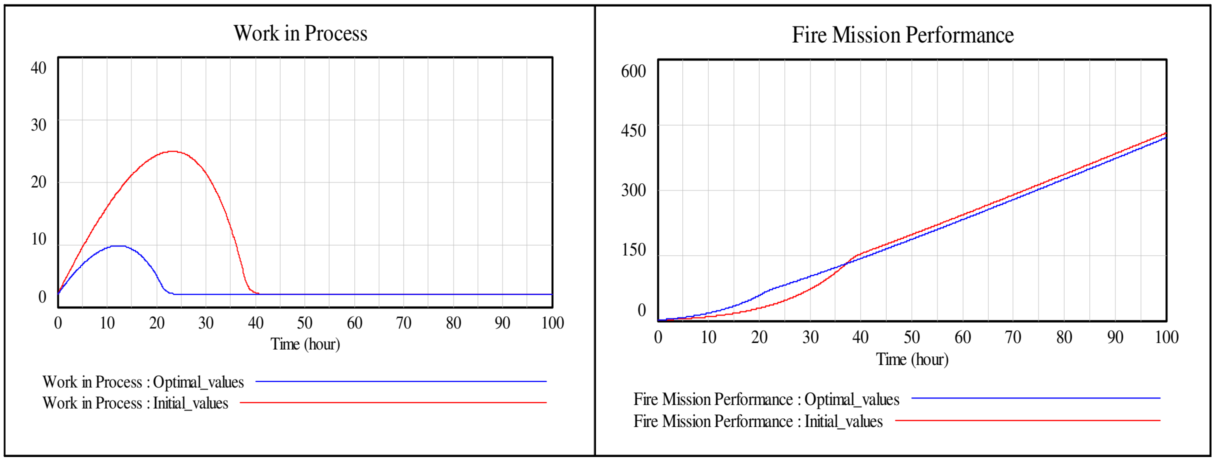

Figure 9: Comparison of Work in Process inventory and Fire Mission Performance before and after the optimization

4. Conclusions

Knowledge is clearly one of the most important strategic resources to remain competitive and firms need to both create it and manage it. But effective decision-making in environments of dynamic complexity requires expanded analysis and models that can describe these complex behaviors. The proposed framework uses knowledge complexity as a more appropriate method to measure the value of intangible knowledge processes. From there it performs analysis of process alternatives based on their interactions, feasibility and the stability of a system with modified and/or new processes. The framework then models the structures and feedbacks that take place in processes while applying a knowledge valuation methodology as its mathematical basis. The existing literature does not analyze interactions of knowledge processes before changes are made and neither does it model the resulting systems in a dynamic fashion for the purposes of controlling and comparing process variables. The proposed framework methodologically selects candidate processes, studies their interactions, and dynamically models the value added by knowledge for alternative decision making. The structured combination of existing methodologies proposes a means to understanding how process investments affect value-added while dynamically providing return on investment.

Acknowledgements

We would like to express our great appreciation to Dr. Thomas Housel of the Naval Postgraduate School for his valuable and continuous support during the planning and development of this research work. His availability and willingness to offer his time has been very much appreciated.

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