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THE EFFECTS OF COMPLEXITY ON BUSINESS PROCESSES REENGINEERING: VALUES AND LIMITATIONS OF MODELING AND SIMULATION TECHNOLOGIES

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ABSTRACT

This paper argues that the value of simulation and modeling technology tends to be contingent on creating models that can offer a systematic, well defined way of representing the structure of a firm's business processes. As such, the behavior of the stable systems can be predicted through modeling and simulation. Stable business processes can reach an equilibrium over time. Complexity (hierarchical processes) and random changes within complex processes, however, tend to create dynamic systems that have a tendency not to reach an equilibrium. Hence, simulation and modeling of complex and dynamic systems tend to add less value in predictability of such systems.

1 INTRODUCTION

Greater needs for efficiency and global competition have pressured structurally complex corporations to technologically and strategically adapt to radically changing market conditions. In order to achieve strategic co-alignment within increasingly complex and dynamic industry environment, corporations are required to develop core competencies in data-based evaluation and simulation of existing business process performance. The application of information (Modarres & Bahrami, 1997) and simulation (Nylor, Balinfy, Burdick & Chu, 1966; Profozich, 1998) technologies enhance corporations' capabilities to achieve in-depth understanding of internal process performance, and correct allocation of resources. Moreover, systematic data collection and dynamic modeling and simulation of business processes enable top management to examine potential scenarios such as radical reengineering of business processes, prediction of the outcome of reengineering strategies prior to implementation, and the analyses of process reengineering at macro and sub-process levels and their effects on the cross-functional processes.

For the past decade increased expectations for higher performance within domestic and global markets (Hammer & Champy, 1993) have pressured a great number of corporations to undertake numerous improvement strategies through reengineering business processes, downsizing (McKinley, 1993), total quality programs, and innovation (Mone, McKinley & Baker, 1988). According to Hammer and Champy (1993), pressures for higher performance tend to create crisis. Corporations response to such performance crisis tend to be through strategic change, administrative reorganization (Modarres, 1998) and reengineering of business processes. More recently, researchers have posited that reengineering strategies enhance industrial firms' capabilities in reducing operation costs, cycle times and produce high quality products and services (Roberts, 1996, Hammer & Champy, 1995). Moreover, business process reengineering is of significant benefit to strategic leaders in creating value for customers (Hitt, Ireland & Hosskisson, 1996). A number of elements such as structural arrangements and lack of appropriate technologies enhance the risk of failure of reengineering strategies. Past researchers have argued that the risk of failure in reengineering efforts increases due to the lack of leadership commitment, resistance to change and the lack of administrative skill in managing process change (Hammer & Staton, 1994). The risk of failure may also be positively influenced by the lack of proper information technology, poor communication mechanisms, and proper diagnosis of process performance, particularly within complex and hierarchical business processes.

Contrasting views on the effects of radical reengineering on corporate performance and the degree to which corporations should allocate resources to the analysis of existing processes have led to two polemic streams of research shaped by researchers. A number of

authors have argued that radical reengineering of complex processes tend to be contingent on availability of valued resources, managerial capability to fundamentally rethink and redesign business processes (Hammer & Champy, 1993), leadership commitment to change (Hammer & Stanton, 1994), and changes in existing corporate culture (Roberts, 1994). This body of knowledge has focused on the effects of process reengineering on corporations' performance. In this view, reengineering enhances the overall corporate performance and facilitates a systematic review and redesign of critical business processes (Wright & Noe, 1996). Moreover, radical reengineering of business processes improves process efficiency and, identifies and redesigns activities that cross functional lines (Render & Heizer, 1997).

Shifting the perspective, and representing merely another side of a complex relationship researchers have centered attention on the magnitude of change and negative effects of process complexity on corporations' performance. In this view, detail analysis such as systematic data collection and in-depth knowledge of the existing process (e.g., cost and performance) tends to be a wasteful activity, misallocation of resources (Hammer & Stanton, 1994), and increase the risk of failure. Moreover, understanding the actual performance of existing capabilities, objective analysis of process performance and complexity of cross-functional processes creates great difficulty in true assessment (Roberts, 1996). The above research indicates that reengineering tends to increase the probability of failure, and has a negative impact on internal performance and external customers. Although this body of work acknowledges the importance of information technologies, it does not, however, recognize the value of process modeling and simulation and decision support systems (information technologies), detail analysis of existing processes, and how such technologies can enhance corporations' capabilities in implementing reengineering strategies.

While researchers have made significant advances in identifying factors that contribute to success and failures of reengineering, several important issues remain largely unexplored. First, researchers have not considered the effects of process complexity on implementation of reengineering strategies. Complex processes tend to be hierarchical and cross-functional. Another serious omission in the past research centers on the effects of information, simulation, and modeling technologies in capturing essential elements and causal relations to predict the behavior of the complex and hierarchical business processes prior to the implementation of reengineering strategies. Moreover, previous researchers have not addressed how such technologies can enhance industrial firms' capabilities in implementing radical or evolutionary reengineering strategies. Complexity (hierarchical processes) and random changes within complex processes tend to create dynamic systems that have a tendency not to reach equilibrium. Hence, the values of simulation and modeling of complex and dynamic systems in predictability of such systems are unclear. The present research seeks to explore whether process complexity and variability influence the implementation of reengineering strategies. Moreover, this research develops theoretical arguments on the values and limitations of simulation and modeling technologies in measuring process performance and implementation of reengineering strategies.

The present research is organized in the following order. The introduction provides a review of relevant literature on complexity and hierarchy within business processes. The issues concerning reengineering business processes and effects of complexity on reengineering processes are discussed in section two. Section three focuses on the value and limitations of modeling and simulation technologies and in reengineering business processes. Section four describes the future research and concluding remarks.

2 THEORY AND HYPOTHESES

Effects of Complexity on Business Process Reengineering: A business process is the creation of value to internal and external customers through collection of tasks and activities that takes one or multiple inputs and creates a single /multiple outputs. A business process is an important variable in understanding the nature and interrelation among activities within complex corporations. Davenport and Short (1990) defined business process as a set of causal and logical interrelated tasks performed to achieve a determined outcome. According to Davenport (1993), processes can also be defined as a set of activities that are structured (e.g., cross functionally, or hierarchically within a particular function) and measured to produce a specified output for both internal or external customers. Within corporations with complex structures, business processes tend to be inter-connected with other internal processes. As such, adjacent cross-functional sub-units tend to use the process outputs as their input.

Structurally complex corporations support and maintain greater numbers of interrelated and hierarchical processes. Large corporations contain complex and cross functional business processes that are divided into autonomous, semi-autonomous, sequential, or concurrent sub-processes. According to Simon (1982), complex systems are composed of interrelated sub-systems, each of the latter [sub-systems] being in turn hierarchic in structure until the lowest level of elementary sub-system is reached. Within the complex hierarchical processes, the sub-processes are subordinated by a functional relation to the macro business process it belongs to. As such, complex hierarchical processes are analyzable into successive sets of sub-processes and the introduction of radical

reengineering affects both macro processes and their subordinated sub-processes. The sub-processes within hierarchical systems are nested within macro processes. As such, variations and changes resulted from sub-system interactions will be manifested at the macro level processes. Hence, the greater the possibility for vertical process decomposability the higher the level of complexity. Moreover, within a dynamic system variability of the macro processes tend to be influenced by interactions and changes of the sub-systems. The complexity of hierarchical processes, therefore, create great difficulty in fundamental redesign within such processes and predicting the outcome of drastic reengineering. Moreover, the dynamic interactions within micro sub-processes create a number of problems that may enhance the probability of failure. The complexity of hierarchical processes tend to reduce the possibility of identifying the risks attached to drastic reengineering. That is, the impact of change on other cross-functional processes and the likelihood that a particular risk event will occur (Roberts, 1994). Hierarchical processes also tend to have a negative influence on the selection of the right process to reform.

Proposition 1: The complexity of hierarchical business processes, tend to negatively affect radical reengineering strategies.

The center of the debate in reengineering processes tends to be the reallocation of existing resources necessary for the documentation and detail analyses of the existing processes. Past researchers have indicated that extensive and detailed analysis and documentation of existing business processes are misallocation of existing resources and irrelevant to reengineering initiative. According to Hammer and Stanton (1994), reengineering is initiated to correct for the performance shortcomings of the existing processes. As such, the underlying assumptions that shape the processes ought to be replaced by new assumptions. The authors also remarked that teams chartered to analyze the performance adequacy of existing processes may engage in political activities and maintain the status quo and power bases, and resist reengineering. Moreover, reengineering, in this view, identifies and discards the element of process complexity and disposes of the complexity assumption.

Understanding the behavior of existing processes under various conditions, however, can be instrumental in gathering appropriate metrics and identifying duplication of activities, and the low performance processes. The causal connection within hierarchical processes, and the assessment of the micro level variability and changes on macro processes tend to be essential in reengineering strategies. Complex processes tend to be sequential and interrelated. Such sequential and integrated business processes require greater degree of coordination for change and reengineering. Sequential business processes are complex and necessitate greater coordination and planning as the output of one process serves as an input for another. That is process "C" can be performed after successful completion of its preceding process "B" which in turn rests on process "A" and so on (e.g., Thompson, 1967). Within such systems low process variations through repetition facilitate proportional allocation of the resources based on process capacity and construction of complex work flow arrangements. Similarly, integrated systems tend to be complex. Dynamism and variations resulted from micro (sub-systems) interactions within integrated business processes create difficulty in implementing radical reengineering without increasing the risk of failure.

Proposition 2: Complexity and variability within hierarchical processes tend to increase the risk of failure for radical reengineering.

3 THE INFLUENCE OF MODELING AND SIMULATION TECHNOLOGIES ON REENGINEERING STRATEGIES

In this section we describe whether static (process models) and dynamic (simulation) analyses enhance the industrial firms' capabilities in analyzing existing process performance and coordinating reengineering process. This section will also focus on the values and limitations of process models and simulation technology in reengineering complex hierarchical business processes.

Process complexity and static analysis: values and limitations of static modeling: Understanding business processes is contingent on creating a methodology that enables us to analyze integrated processes. Both modeling and simulation technologies facilitate a greater learning about business process architecture and assess the behavior of business processes under various conditions. Process models facilitates a systematic approach to documenting, and representing the static structure of the business process. Process models also enhance the knowledge base about the causal connections between the macro and micro (sub-processes). Industrial and service firms use process models as a means to identify the missing information links, rework cycles, strategic and tactical change and their impact on the current process performance. According to Busby and Williams (1993), process models identify the structure of the current operations and provide valued information on instituting a self adjustment mechanism for process improvement. The authors also indicated that process models permit process owners and managers to identify inadequate connections between activities and information systems, duplications of activities, and the creation of a macro model about cross functional interconnections. Similarly, Hammer and Champy (19993) indicated that success in process reengineering can be attributed to the creation of the flow charts, spread sheets and process models. Hence, analyzing the static process

models reveals information on the effectiveness and degree of certainty an industrial and business firm operates.

Figure 1 illustrates a macro level process of how customer requirements are defined, and how design engineers create geometric drawings based on customer requirements and existing technology for manufacturing. The process illustrated here is a collection of both sequential and concurrent activities within various business units and cross-functions. The macro level process also establishes the fundamental facts about market (customer requirements) and internal requirements (technology and resources). As indicated earlier complex processes tend to be hierarchical, and can be viewed and analyzed at various levels of detail. Figure 1a, shows that each activity within the process has a number of sub-processes. That is, market requirements consist of industry analysis, competitive analysis, and the latest technology. Define activity consists of basic requirements to identify whether current technology can facilitate manufacturibility. Moreover, at a micro (sub-process) level analysis of process model can reveal the strength and the weaknesses of the existing processes. The micro models are valuable to analysts in identifying critical information about the ordering of the activities within a process (sequential and concurrent activities), decision points, and missing elements such as self-check activities for process improvements, communication mechanisms among various teams, or the need for new information systems to improve the existing process.

The analysis of the static model tends to constrain the analysts to capture the real behavior of the system, and assess the influence of variability on system's performance. Profozich (1998) argued that static tools and models are incapable of dynamic analysis. As such the static tool may reflect an optimistic view of the system's performance. Profozich also indicated that increased variability within a system generates greater errors in static analysis. In order to capture the true system's behavior under various conditions, all the possible scenarios ought to be considered. That is, the effects of randomness and variability ought to be measured at macro and micro levels within hierarchies. Static process models and tools have great difficulty in assessing system's performance. The shortcomings of static models in conducting dynamic analysis can be categorized in the following ways. First, static models are not capable of considering variability and randomness and process capability to respond to change. The static process models do not provide sufficient information to identify detailed deficiencies in the hierarchical processes and the costs involved in correcting such deficiencies. Second, the effect of variability and randomness at various levels of hierarchy and the collateral impact on adjacent processes cannot be determined through static models. Third, static process models lack the capability to assess the impact of process reengineering prior to implementation (proof of concept). Busby and Williams (1993) argued that the information offered by static process models may not be novel in nature. That is, static models provide a snapshot of the dynamic process and are unable to predict system's behavior. In predicting the system's behavior under various conditions it is necessary to be able to introduce the variability in the environment and in each process. According to Profozich (1998) the assumption that each process will operate on the average is not sufficient. Moreover, in order to identify bottlenecks, trends, and resource allocations a dynamic analysis of business process performance is necessary. ***Proposition 3: The greater the process complexity and variability the greater the difficulty in predicting systems behavior using static process models. Proposition 3a: The greater the process complexity and variability the lower the value of static modeling in implementing process reengineering strategies.***

Process complexity and dynamic analysis: values and limitations of simulation technology: Simulation Technology enables industrial firms to consider variability and randomness in their business processes. Consideration of the variability and randomness enhances firms' capabilities to capture the behavior of the processes under various conditions (e.g., various "what-if scenarios). Moreover, simulation technology can influence the nature of the decision made in a firm as well as the decision-making process. Historically, the process design and optimization has been accomplished through static modeling; simulation allows greater flexibility in model validation and change in a dynamic fashion. Such dynamic analysis provides an opportunity to test for unexpected interactions within the system or check the robustness of the design (Swain, 1995). Simulation allows industrial firms to formulate their operational strategies based on process optimization. Swain (1995) remarked that simulation can be considered as a vital component in modeling the enterprise-wide modeling, in which processes once treated as separate functions (e.g., manufacturing, sales, design) can be modeled as a group and optimized as a system.

Profozich (1998) argued that variability and "moving time clock" identify the process capability under various conditions. The author indicated that variability tends to have a ripple effect on the decision making processes. The businesses tend to have greater numbers of conditional decision making and process interdependence that dramatically amplifies the effect of variability within the business processes. Moreover, Profozich (1998) argues that the combination of one moving time clock and dynamic decision making within the processes creates a chaotic environment that can negatively influence the performance significantly. ***Proposition 4: The greater the process complexity and lower the variability the higher***

the value of simulation in implementing reengineering strategies.

Effect of randomness and variability on complex processes: Typically randomness enters a simulation model in 3 ways: (1) in the modeling of interarrival times of new entities into the system, (2) in percentage routing of items to different processes or subprocesses, and (3) in modeling the flow times of individual process steps.

A random variable such as a cycle time for a whole process or subprocess will be a combination of the random variables for the individual process steps. (This discussion will concentrate on process cycle time, although it is applicable to any outcome of a process that is the sum of outcomes of process steps.) These random variables combine through summation, extreme values, and mixture. Summation is, of course, the adding up of values of random variables from successive, sequential process steps. The cycle time of a simple sequential process will be the sum of the cycle times of each of the steps of that process.

An extreme value combination of random variables occurs when an item enters a set of parallel processing steps but cannot continue until all of the processing steps are complete. For example a new customer may request to be routed simultaneously to multiple Engineering departments for initial review before a response can be made.

Mixtures of distributions occur wherever there is a percentage routing or feedback loop. If a subprocess has a percentage of items passed on to the next process step and the remainder sent to rework, the cycle time for that subprocess will have a mixture of two distributions, that of the normally processed items and that of the reworked items.

These three methods of combining random variables each produce different results. Summation tends (under rather broad conditions) to produce random variables that are approximately normal, even though the the components of the sum may not be normally distributed. The cycle time of a sequential process that is the sum of many steps, each with a small contribution, would therefore be expected to be approximately normal with mean and variance equal to the sums of variances of the components.

Extreme value distributions, on the other hand, tend to be highly asymmetrical. If an extreme value distribution makes up a large portion of the distribution of a process cycle time, this will tend to make the process cycle time asymmetrical also.

Mixture distributions are the least likely to resemble standard mathematical distributions and to exhibit such features as multimodality. Use of simulation to predict the range of possible values from such a distribution (as opposed to estimates of the mean) will require a large number of replications in order to form an empirical distribution function.

A process may be complex in two ways: having a large number of steps or having a complex set of percentage routings and feedback loops. To the extent that complexity consists of simply a large number of process steps, the process cycle time is likely to be approximately normal. The process should be predictable through simulation; however the ranges of prediction will depend on the overall process variance. On the other hand, a process with a complex network of feedback loops is likely to produce a complex distribution of overall cycle time. The distribution of such a process can be estimated by forming an empirical distribution function, but this will typically require a very large number of replications.

Process complexity and the adequacy of a model: A simulation model will typically provide predictions of process behavior and of the variability of that behavior. The adequacy of those predictions depends on how well the model reflects the process. A model may err in depicting a process either through errors in specification of process step distributions or in missing whole process steps or feedback loops. To the extent that a model fails to show all the steps of a process, any estimate of process variability will be only a lower bound on the actual process variability. Process complexity makes the collection of adequate process information more difficult and increases the chances of a model that does not capture all elements of the process.

Figures 1, 2, and 3 illustrate the types of combination of random variables in a simulation model. In these figures consider the value of cycle time, which is random according to some distribution in each step. In Figure 1, the process steps occur sequentially. The cycle time for an item going through the four process steps pictured will be a simple sum of the cycle times of each of the processes. Where there is a large number of sequential process steps, each contributing a small amount to total cycle time, the cycle time for the overall sequence should follow a distribution resembling a normal distribution.

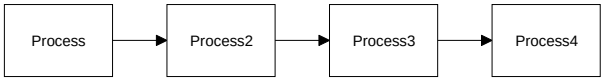

Figure 1. Sequential process steps.

In Figure 2, an item leaves Step A and is split into items which are processed *concurrently* by steps B1, B2, B3, B4, and B5. Further processing in Step C cannot take place until all of B steps have completed. The cycle time of the B steps is therefore the cycle time of the slowest B step, an extreme value. The distributions of extreme values of random variables tend to be highly asymmetric, not at all like normal distributions.

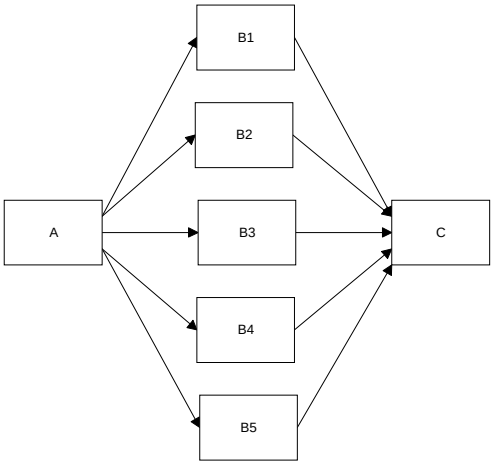

Figure 2. Parallel processing (Extreme value).

In Figure 3, an item is processed in Step A. A fraction a of the items are sent back to Step A for rework. If rework takes as long as the original processing, the cycle time (ignoring items which are reworked twice) for an item to successfully complete Step A will be equal to the cycle time for Step A with probability 1 - a. With probability a. the cycle time will have the distribution of running Step A twice. This is a *mixture* of distributions and may take on a variety of mathematically inconvenient forms. For distributions that have density functions, a mixture of two distributions will have the density function:

$$p_1 f_1(x) + p_2 f_2(x)$$

where f_1 and f_2 are density functions and $p_1 + p_2 = 1$. The mixture can be interpreted as the distribution of a random variable which with probability p_1 takes the distribution with density f_1 and with probability takes the distribution with density f_2. For a mixture of k distributions that have density functions, the density of the mixture will be:

$$p_1 f_1(x) + p_2 f_2(x) + \ldots + p_k f_k(x)$$

where $p_1 + p_2 + p_k = 1$.

Although the mathematical representation of mixtures is simple (assuming that the component distributions are mathematically simple), these distributions tend to have multimodality (multiple modes) and heavier tails. The tails of a mixture distribution will tend to be of the order of magnitude of the component distribution with the heaviest tails.

Because so many business processes modelled by simulation involve feedback loops and percentage routing, mixtures will tend to be a significant part of the distribution of any variable that is an aspect of an entire process. For this reason, if one wants a view of the actual distribution of such a variable (as opposed to a mere estimate of the variable's mean), one should run a lot of replications, enough to gain a view of an empirical distribution function. It should be no surprise if such a distribution function is multimodal or otherwise irregular.

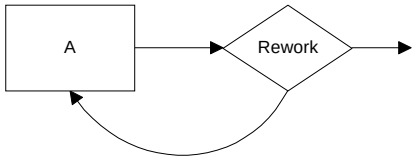

Figure 3. Rework (Mixture distribution)

Hierarchical Processes integration: The parallel process in figure 2 and the re-work in the figure 3 can be integrated in a hierarchical fashion (sub-processes) to each of the processes in figure 1. The complexity of such integration create a difficult simulation model. The predictive capability of such a model would greatly depend on the correct metrics on proper distributions, costs, efficiency, cycle time and the distribution of incoming items. This hierarchical model will also include a mixture of distributions and may create a variety of mathematically complex forms. Modeling such complex processes may not fully describe all the relevant relationships of a business situation. Moreover, the simulation of such models will only give predictions surrounded by so many limiting conditions that decision maker will be prepared to reallocate resources based on such predictions. Hence, the more complex the process and the greater the mathematically inconvenient forms, the more difficult it will be to model, simulate and predict the behavior of the process under various conditions. ***Proposition 6: Process complexity and randomness increases the range of variability in simulation models and reduces the value of simulation in predicting systems behavior.***

4 CONCLUDING REMARKS

We discussed how process complexity and hierarchy influence the process reengineering strategies. It was argued that static modeling technologies are not capable of performing in-depth analysis and predicting the behavior of the system under various conditions. Dynamic systems change frequently both at micro and macro levels. Static modeling technologies are not capable of assessing the need to make changes. Moreover, process variability reduces the usefulness of static models in assessing the impact of change on cross-functional processes and sub-processes (hierarchies). Simulation adds greater value to the understanding and reengineering the business processes. However, as the complexity, randomness and variability within business processes increases the predictability of process behavior under various conditions becomes more problematic. That is the range of predictions becomes too wide for a decision base. Future research should concentrate on empirical study to test the propositions developed in this paper. Moreover, future

researchers should develop information systems that are designed to integrate several technologies. Such integrated technology will facilitate the creation of information repository integrated with simulation, modeling, and other ODBC compliant databases.

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