MODELING & SIMULATION
IN BUSINESS PROCESS MANAGEMENT

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SIMULATION AND BUSINESS PROCESS CHANGE

Simulation is a tool for managing change. Practitioners in business process management know the critical importance of carefully leading organizations and people from old to new ways of doing business, and simulation is one way to accelerate change. This capability derives largely from the ability of simulation to bring clarity to the reasons for change. Simulation provides more than an answer: it shows you how the answer was derived; it enables you to trace from cause to effect; and it allows you to generate explanations for decisions.

Simulation is a component of a business rules engine. You can view simulation as a solution to both off-line design and on-line operational management problems. Engineers derive rules from the mental models experts provide on how their processes work and how to make decisions that will help them forecast how a change might impact those decisions. Formalizing and simulating these models makes the automation of business rules more robust. In the design of new business rules, simulation provides a way to validate that processes will work as designed.

Simulation enables the successful use of organizational improvement programs such as Six Sigma. The activities of define, measure, analyze, improve, and control depend on the earnest participation of everyone involved to manage quality. In particular, the last three (analyze, improve & control) revolve around identification of root causes, coming up with new policies and practices, and putting controls in place to keep quality high. Clearly, simulation can play the important role of reducing the risk of change and managing change

This article presents background material on simulation, its relation to modeling, the technology of simulation, and some practical applications in business process management.

SIMULATION EXTENDS BUSINESS PROCESS MODELING INTO VALIDATION

Modeling is a tool for representation. Models define the boundaries of the system you want to simulate. Business process modeling practitioners and software vendors have created a wealth of formalisms, software tools, and methodologies for understanding what to model, how to model, and ways to conduct analyses with models. The articles published on this website provide many examples of these tools of the trade. Modeling is a necessary component of any simulation, but it is not sufficient for conducting a simulation. To simulate, one needs a simulation engine, which is described in the section below.

Models for simulation can be simple or complex. Some modeling and simulation tools allow you to create detailed models of business processes with a high degree of fidelity to actual processes. Other simulations are simple calculations of indicators or metrics. While it seems reasonable that a high-fidelity model would be the best, this does not mean that the model must be complex. A common mistake in modeling and simulation is to build an overly complex model, resulting in an over-abundance of data and great confusion in analysis of the results. If the model doesn't represent the behavior of the system of interest, it is useless for analysis of that system; in addition, overly complex models are unwieldy, slow, and difficult to analyze. Simulation experts are effective at finding the right model size and complexity needed to represent the problem to be addressed without unnecessary detail. The key facility that experts develop is an ability to distill real-world problems and extract the essence of the problem so that it can be modeled simply, but still retain the dynamic behavior needed to examine important problems. Some tools aid the user in this task by providing templates or guides that encapsulate this expertise.

Simulation is a tool for time and space compression, both of which are needed for robust validation. Successful business process transformations are those that have withstood the test of time and solve real problems. They have been validated through months or years of operation with a demonstrated return-on-investment. New implementations of these processes aren't risky because users know they will work as expected. However, when a new or innovative process is devised, it's impossible to tell whether an asserted ROI can ever be realized. Simulation provides a mechanism for robust validation under realistic conditions and can substantially reduce the risk of deploying a new process.

Validation of a business process can be done in many ways, but a structured method for examination involves a series of qualitative or quantitative experiments. A business problem statement identifies the variables that experimenters change, as well as the metrics that indicate success or failure, and the validation exercise is completed through a series of simulations. Pilot projects with limited data sets, conducted in low-risk laboratory environments, provide data that support cost/benefit analyses.

Since there are a large number of possible alternatives, simulations are limited by a careful selection of variables and the application of design-of-experiments techniques. The hard constraints are time and space, and achieving a compression of both can only be done one way – through modeling and simulation.

TYPES OF SIMULATION MODELS

Simulation is used to describe a broad range of capabilities. By definition, these all involve reproducing or projecting the behavior of a modeled system. Computer-based simulations can involve everything from simple addition of a few numbers to intensive computations that challenge the fastest computing machines currently available. Models for simulation can be classified along four distinct dimensions:

System of Interest – The system of interest can be one of the following:

- *a physical system,* for example, a supply chain or production line,
- *a management system,* for example, a CRM process, or
- *a meta-model,* for example, rules that establish whether a model is formulated properly.

Visibility – Internally, a model may be:

- *transparent*, that is, a description of actual mechanisms, or
- '*black-box'*, that is, a description that results in the same behavior as the real system but internally does not model the actual mechanisms.
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Probability – A model can be

- *probabilistic,* that is, a single set of inputs that results in many possible outputs--the outputs exhibit variations that are described using statistics, or
- *deterministic*, that is, the same set of inputs results in the same set of outputs; the outputs are causally determined by preceding events.

Dynamics – A model can be

- *steady-state*, that is, the outputs show no variation over time and space, or
- *dynamic*, that is , the outputs vary over time and across space.

SYSTEM OF INTEREST

The system of interest determines the kind of information generated in a simulation. Simulation of business process models is not the same as simulation of the underlying physical system that the business processes manage. In a supply chain simulation, it is necessary to model the physical system, that is, the movement of material from node to node in the supply network. This allows us to understand the dynamics of inventory movement, bullwhip effects, etc. Sometimes the physical system is the focus of the simulation effort --to determine, for example, the best location for a new distribution center, or to understand the differences in machine performance in a production line. In other cases, the system of interest is the management process, including the data used in the process. For example, call center process models have been used to understand hardware and human resource requirements and how best to deal with peak call periods. Meta-model simulation is common, for example, in checking the configuration or connectivity in graphically constructed models; simulating 'a model of a model,' is useful when the focus is on the mechanics or architecture of constructing models, rather the behavior of the model.

VISIBILITY

Visibility of model structure is increasingly important to the business community. Business managers want explanations of automated decisions, and implementing this capability requires visibility into model structure. Still, in many situations, it is essential that a model provide only an answer - and the faster it can do so, the better. Data-driven models, including common regression models and more general neural network models, suit this purpose well and can be prepared quickly if there are sufficient data to identify the internal model structure. These black-box models come with their own learning procedures and have been widely applied in practice because they are easy to use and highly effective. But these models hide the manner in which a result was obtained. In this sense, they are much like a human brain; that is, we don't always know the inner workings of a particular reasoning process, but we know that it occurs with great efficiency and regularity. Black-box models learn repeating patterns and correlations among data and have their own internal way of representing these relationships. The internal representation may provide few or no clues as to the causal chain that resulted in the observed model behavior.

In contrast, transparent, mechanistic models are descriptions of the actual processes that occur, based on natural laws and scientific principles. Models of the trajectory of a missile, a known chemical reaction, or the replenishment of inventory are transparent in the sense that modelers can refer to the structure of the model itself to gain insight into the behavior that the system exhibits. The parameters in mechanistic models have specific meaning that can be interpreted in terms of the real system to better understand why a particular result was obtained. With this kind of model, it is possible to automate the generation of explanations and to identify root causes of an observed behavior.

PROBABILITY

Probability plays an important role in simulation just as it does in real life. Models of reasonable size and complexity exhibit a set of possible behaviors that, in general, are unknown unless the model is simulated. Models also have validity constraints that identify when they are good representations of the real world and when they contradict or incompletely describe the real system. In order to understand the range of possible behaviors, it would be useful to simulate the model under all possible conditions. However, this is impractical, except for the simplest models. Instead, practitioners use techniques such as Monte Carlo analysis. In this technique, sets of model inputs are sampled randomly from statistical distributions to define multiple simulation scenarios. The scenarios are simulated, and the results summarized statistically to create an overall understanding of the range of behaviors that can be realized with the model. Any of the types of models described above can be made stochastic by randomly selecting parameter values each time a simulation is run. For example, a business process model that includes an average value for 'order processing time,' might, instead, sample the order processing time from a normal probability distribution with a predefined mean and standard deviation. Without the randomness, the model is deterministic; that is, the simulated order processing time will always be the same, regardless of how many orders are processed.

DYNAMICS

The remaining modeling dimension – dynamics - is the most important. Developing models is a challenge, but many models used in practice are static or steady-state models, rather than dynamic models. Formulating a model that can show the change of important business metrics over time or across space (e.g., geographically) is a unique challenge. Most spreadsheet models are static in nature, as are simple aggregations or data consolidations that are sometimes described as simulation. Steady-state models are valuable, but they hide or gloss over the actual behavior that occurs in a real, dynamic process. For example, many stock-out conditions that occur in supply chains are caused by sudden changes and demand swings, and the bullwhip effect is due in part to time delays that limit visibility into important information.

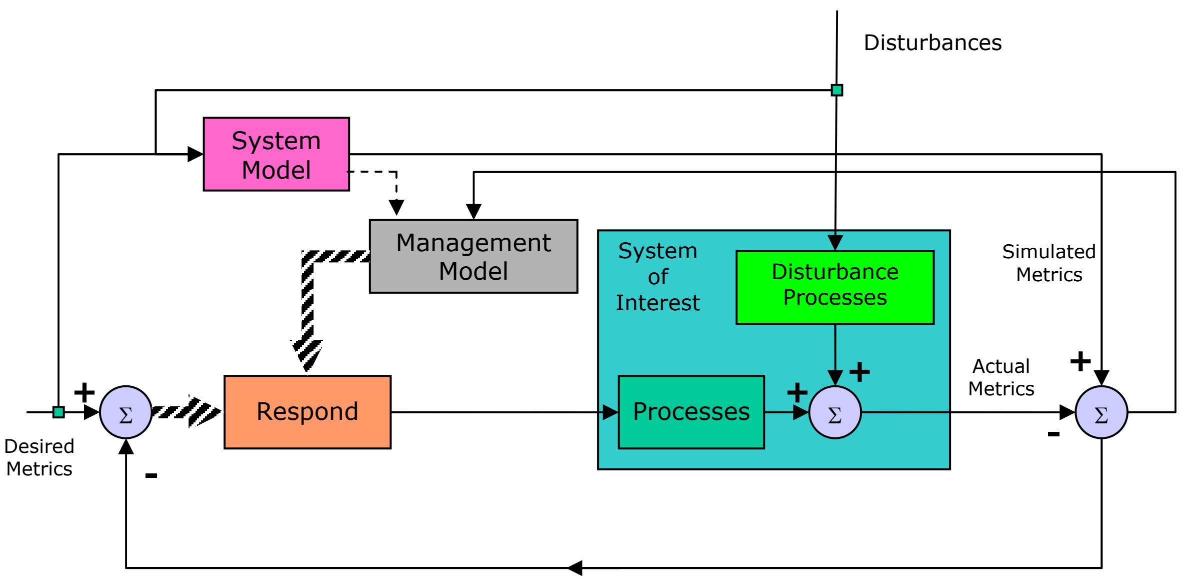

Figure 1. System models and management models work together in a real-time setting.

Models can be used off-line or on-line. Some modeling tools contain specialized support for on-line use. In off-line analysis, a model is constructed, calibrated, and simulated without the need for connection to real-time data or events. Strategic and tactical planning exercises make use of modeling and simulation, but the time frame for decisions is long (on the order of weeks or months) so it's sufficient to work in batch mode, collecting data from databases when needed, conducting the analyses independently, and publishing a report on the results. Operational applications of models require support for events, transactions, and persistence. These features add a lot of overhead and infrastructure to a model, but are essential to the implementation of simulation capabilities in the real-time, event-driven world. Figure 1 shows how a model of the physical system and a model for managing that system work together in real time. A simulation of the System Model runs in parallel with the System of Interest. Actual and simulated metrics are compared and evaluated in a Management Model that identifies steps to take to respond in a manner that drives the system metrics towards their desired values. The two bold-striped arrows highlight the fact that the architecture supports both automated and, by disconnecting the arrows and inserting a human decision-maker, manual use.

SIMULATION AND OPTIMIZATION

A common question asked about simulation is: What is the difference between simulation and optimization? There are both technical and practical answers to this question. Consider the simple equation:

$$y = f(x)$$

In this equation, x represents the input to a model, the model is represented by the function *f*, and y is the output of that model. For example, x may be the replenishment target for an inventory management process, *f* a model of the replenishment process, and y the level of inventory that results. Both optimization and simulation may be used to explore the behavior of the function or model *f*.

One way to understand the behavior of the function *f* is to conduct 'what-if' simulations by entering different values for x and then examining the values of y that are generated as output. That is, what is the value of y if the value of x is '5'? In a realistic situation, there may be many inputs (x) and outputs (y), and the nature of the function (*f*) may be complex.

Another way to understand the behavior of the function *f* is to conduct 'if-what' optimizations by setting a target value for y, then searching for the values of x that result in the target value for y. That is, if the desired value of y is '10,' what will be the value of x? Again, the number of inputs (x) and outputs (y) may be large, the model complex, and the search techniques can be elaborate.

Optimization is appealing because the result is the value of the model (or, by inference, the real system) input needed to achieve a desired output. Simulation can be used to achieve the same goal but requires effort to simulate many alternatives to find the value of x needed to obtain a target value for y. Thus, optimization gives a direct answer to the question of how to reach a target. However, the models used in optimization are generally simplified, and it isn't always clear why the solution is 'best.' Simulation is appealing, because the models can be rich in structure and detail; for example, they may provide specific information about cause and effect that is essential to explaining an optimum. However, detailed models can take a long time to simulate and are impractical if the model is too big.

SIMULATION TECHNOLOGY

Computer-based simulation requires an engine to drive the calculation of model variables. The two methods for doing simulation are:

- Systems Analysis – continuous and discrete simulations based on mathematical models and numerical methods.
- Discrete Event – discrete simulations based on an event-handling method.

SYSTEMS ANALYSIS

Systems analysis here refers to mathematical methods for modeling based on systems theory developed, starting in the early 1960s. Both continuous time and discrete time simulation models

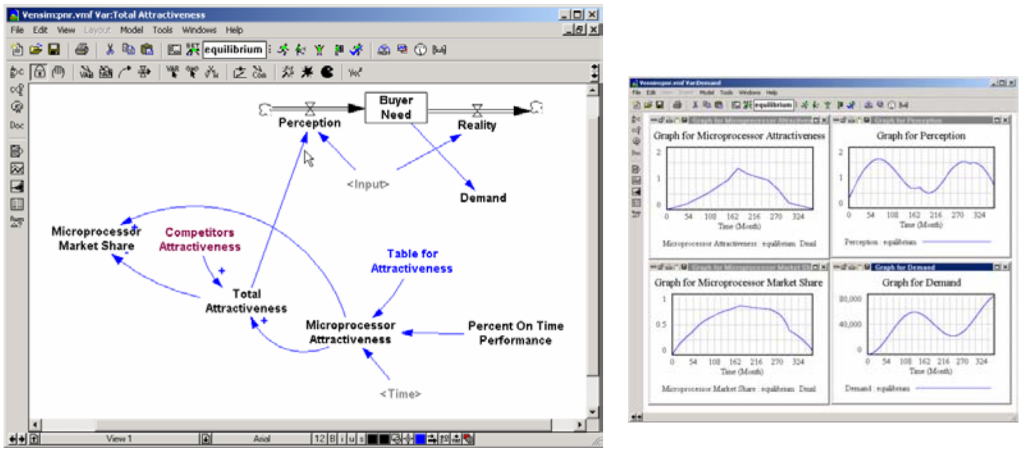

Figure 2. A systems dynamics tool modeling a demand generation process.

can be constructed. Systems thinking and systems analysis methods are elegant and time-tested. In management science, it has spawned the field known as 'system dynamics,' which is both a perspective and a set of tools and methodologies for building simulation models of complex systems of interest. Numerous software tools have been developed to support model building and simulation based on systems analysis. Many of these allow the user to construct models graphically so that the user does not have to write the mathematical equations or fully understand the numerical methods by which the equations are solved during simulation. These tools have made the technology accessible to a wider range of users and created a vast literature addressing numerous engineering and business management issues. An example of this type of model and its simulation is shown in Figure 2. In this example, a model of the process that creates the demand for microprocessors is shown along with the influences that result in buyer need.

DISCRETE EVENT SIMULATION

The discrete event simulation approach is computationally efficient and has the added advantage of being intuitive and, thus, easy to understand. The idea behind dynamic, discrete event simulation is simple. First, a modeler specifies, graphically or in code, the sequence of activities and events that take place in the system of interest. Data inputs are provided and, based on the timing of specified events, an engine time-orders the events in a queue. Simulation consists of popping each event off the queue, then performing whatever activity was specified. For example, to model an order fulfillment process (Figure 3), the user selects task or activity blocks from a palette, connects them together and specifies how often events occur or how long a specific activity takes. In the example shown in Figure 3, telephone orders are emitted from the first block (containing an icon of a telephone) at a rate specified by the user, then pass through subsequent blocks that represent sales, order processing, manufacturing, and distribution. Statistics on activities, costs, and other important metrics can be evaluated.

Graphical construction of simulation models is an innovation that has greatly advanced the use of simulation. Graphical representations can be categorized into two groups:

- 'Block' diagrams – represent the equations and sequence of calculations that in turn represent the system of interest--used with the systems analysis simulation approach
- State diagrams – represent the events and transitions between events that occur in the system of interest--used with the discrete event simulation approach.

An example of the first type is shown in Figure 2. This image translates directly into a set of equations that are solved using the systems analysis approach. An example of the second type is shown in Figure 3. The specification of activities, their explicit connection in a sequence, and the data provided as input, such as event timing and input data, are sufficient to perform a simulation of the model using a discrete event simulation engine.

ENHANCEMENTS THAT INCREASE SIMULATION VALUE

In addition to graphical user interfaces, there are a number of enhancements to simulation and simulation tools that benefit users. These enhancements cover the life cycle for application of a simulation model from definition of the model, through validation and configuration of the model for decision support, to on-line deployment and continuous improvement of the model.

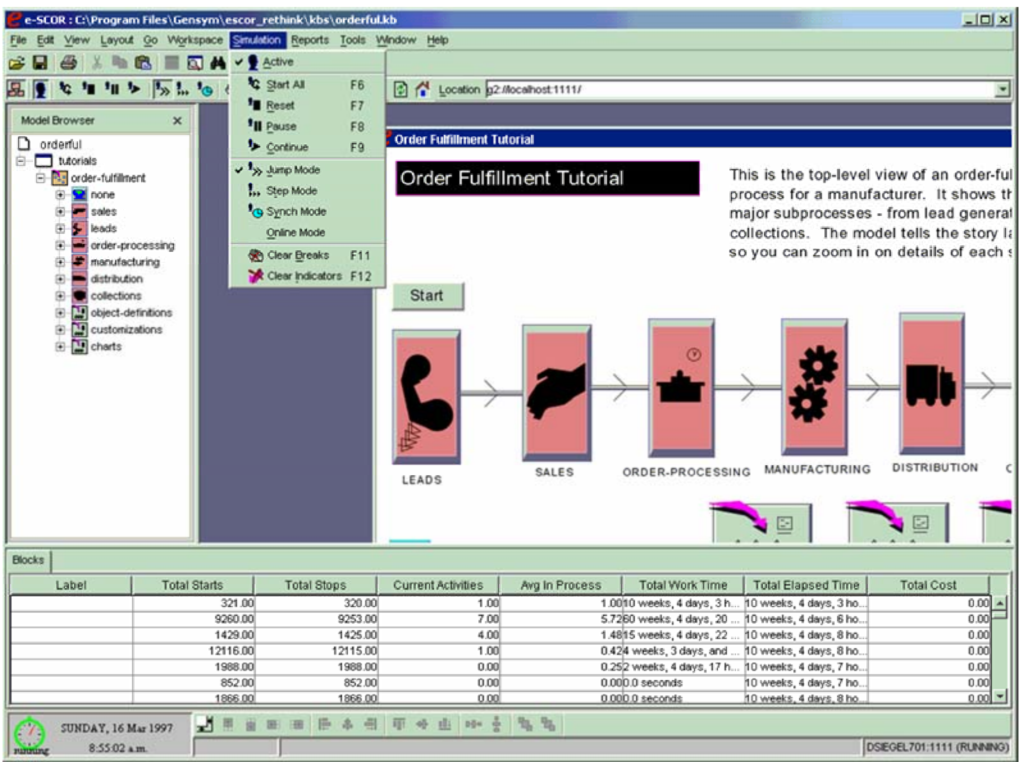

Figure 3. Discrete event simulation of an order fulfillment process.

Model definition challenges include selecting the proper type, identification of processes, establishing the level of detail or resolution, deciding how to abstract processes, and obtaining data for input. Model types must be judged based on knowledge of the pros and cons as described in the sections above. Definition of processes and level of detail or abstraction is aided by tools that either come with templates or allow you to define your own. Reference models and industry standards that define generic processes simplify both modeling and the conduct of simulation studies by making it easier to compare results within the same study or with others who use the same templates or references.

Data collection, reduction, and organization are often bottlenecks in simulation studies. Without instituting controls to manage data, there are pitfalls both on the front-end where users fall victim to data 'safaris,' and on the back end where analysis paralysis interferes with the goal of finalizing results. Depending on the model size, there may be many data elements to collect, and it is common for teams to search endlessly for detailed data that they will never find. The naïve tendency to model everything and to collect too much data dooms many simulation studies to failure.

Especially for large models, it makes sense to organize data input in such a way that you get the model up and running quickly, then let simulation determine what additional data are required. Effective practitioners of simulation have a good understanding of the system being modeled and have structured the data required for simulation such that only a few data elements are needed to get started. This subset of data should be sufficient to obtain good qualitative validation of the model, which can then be followed by incremental improvements, leading to a well-calibrated model. Simulation results can easily fill a hard disk with data, so it's a good idea to first define what you want to analyze, then design the simulation experiments to obtain specific data for analysis.

Design of experiment techniques have been used to structure and organize simulation experiments. These methods are step-by-step instructions for formulating a simulation study and for evaluating the results to demonstrate statistical significance. Some software tools provide guidance in setting up and running simulations within a design of experiments framework. Figure 4 shows a variant of a design of experiments approach. The first step is completed with knowledge of modeling and simulation, but without the need for software tools. Definition of the business problems is essential and directly determines the model parameters that will be varied and the model metrics that will be analyzed.

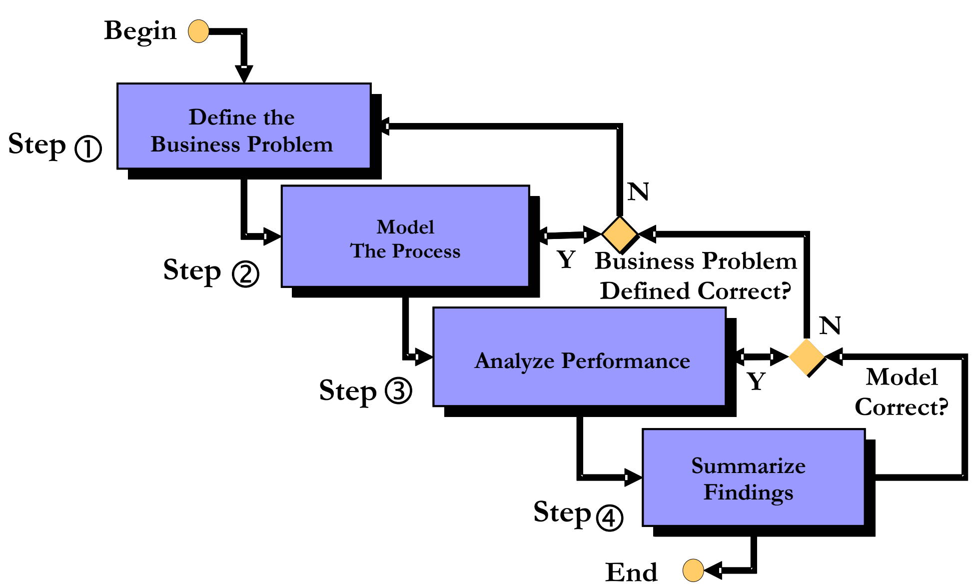

Figure 4. A design-of-experiments methodology.

A problem statement is often posed as one or more questions to be answered through simulation. For example, a business problem statement for a supply chain simulation study might be:

> What **Distribution Center network**, including **order management policies** and **replenishment strategies,** are required to ensure *profitability* and maintain a *95% on-time performance* for delivery of chip sets to global customers assuming a maximum **20% forecast (in)accuracy**?

In this statement the text in **bold** identifies input variables or parameters that we can change in a simulation model, and the text in *italics* identifies output metrics that are observed to determine the impact of the changes. Feedback loops are provided because it is always necessary to ask whether the model is correct and if the business problem is properly defined. A solid design of experiments approach minimizes the modeling and simulation effort and adds robustness to the results.

SIMULATION AT THE DOD

The US Department of Defense has a keen interest in simulation as a tool for forecasting and planning. A good example of their application of simulation is in the Joint Simulation System (JSIMS, www.jsims.mil), whose purpose is to support training by providing an environment indistinguishable to the training audience from the real world. JSIMS applies the DoD's High-Level Architecture (HLA) for distributed simulation. In this architecture, several JSIMS modules, running on multiple machines located in geographically disparate locations, must communicate and stay synchronized. The HLA ensures the necessary synchronization, creating a synthetic battlespace that can be used to create virtual operating scenarios. There are obvious parallels between this type of application and simulation-based decision support systems in business process management. One hi-tech company envisions such a system for management of its entire supply chain and anticipates realizing the architecture of Figure 1 to allow management to foresee the state of the entire network for the purposes of maintaining network health and meeting customer expectations.

WHAT THE FUTURE HOLDS

The Society for Modeling and Simulation International (previously the Society for Computer Simulation) recently celebrated its 50th anniversary with a special issue, describing the history of simulation and predicting its future. Surprisingly, Bernard P. Zeigler, President of the Society, doesn't call for new miracles of technology or envision fantastic advances in modeling and simulation (Ziegler, B.P., 2003, *Modeling & Simulation*, Volume 1, Number 3). Instead, he notes that today's problems are much like those in the past:

> "You might be surprised to find that many of today's hot problems were pretty much of concern from the start and that many of the proposed solutions are really elaborate versions of ideas that originated early on. This realization might be slightly humbling. But on the other hand, the sense of continuity with the past and the future might prove extremely satisfying."

The most useful applications of business process modeling and simulation will likely be those that further elaborate on ideas that have already been explored but, for any number of reasons, have never been fully elaborated. In the same issue, Zeigler also mentions that "…the exponential growth in knowledge we are experiencing is in no small measure due to the growth in computer technology and the modeling and simulation paradigm it enabled." We can now do things with simulation that were unthinkable even a couple of years ago. Examples include the pre-validation, using simulation of re-engineered business processes well before they ever get implemented; the elimination of proposed supply network designs because simulation shows that they will not work; and on-line real-time simulation-based decision support that enables managers and customers to know with confidence that inventory will be available when and where they need it.

The BPM market has seen an up tick in interest in modeling tools that suggests greater acceptance of reference model standards, broader appeal of modeling concepts, and more appreciation for the benefits that can be derived. Simulation is a straightforward extension to static modeling efforts and one that substantially enhances benefits by leveraging existing models and enabling more robust analyses that can be obtained in no other way.