17.7 SIMULATION METHODOLOGY, TOOLS, AND APPLICATIONS

Onur M. Ülgen, University of Michigan-Dearborn and Production Modeling Corporation, Dearborn, Michigan
Edward J. Williams, Ford Motor Company and University of Michigan-Dearborn, Dearborn, Michigan

ABSTRACT

Simulation methods of analysis, supported by increasingly powerful and user-friendly software tools, are gaining increasing acceptance as an indispensable aid to business managers, engineers, and analysts seeking productivity improvements. This article provides an overview of simulation technology and its effective application to process improvement, enumerates and categorizes typical application areas amenable to simulation analysis, and provides case studies as examples.

KEY TOPICS

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1. INTRODUCTION

Simulation modeling and analysis, long the specialized province of mathematicians and computer-science specialists, has entered the mainstream of methods available to help organizations (whether business, governmental, educational, or military) increase their efficiency and effectiveness. The proved abilities of simulation to attack a wide range of problems and investigations rest on its abilities to accommodate stochastic variation, analyze discrete variables, continuous variables, or both, and provide visualization via animation.

In this article, we first enumerate the business motivations for using simulation technology. Next, we compare and contrast simulation worldviews, present an application-oriented simulation methodology, list application areas of simulation, and specify critical success factors. After reviewing available simulation tools, we discuss their integration with allied analytical methods and venture predictions on future trends.

2. BUSINESS MOTIVATIONS

There are many reasons why use of computer simulation has been increasing in popularity in the last twenty years. Some of these reasons are due to the reduction in cost of computers and simulation software, emergence of more user-friendly and powerful simulation software (see Section 7), increase in the speed of model building and delivery, and acceptance of an established set of guidelines of simulation model building (see

Section 6). Other global business-related reasons have increased the popularity of simulation modeling in the last twenty years and these reasons are based on the unique advantages that simulation provides to businesses. These reasons include the following:

(a) ***Increase in Global Competition***. In the last twenty years, pressures exerted on businesses to increase their competitiveness have intensified since almost all businesses can now provide products and services globally. During this time the more productive companies have significantly increased their market share. For example, in the automotive industry, Toyota Production Company has increased its share against its less productive competitors such as General Motors Corporation. The ever-increasing pressure for businesses in implementing continuous productivity improvement, applying business process reengineering for major productivity gains, converting to lean manufacturing and lean supply chains, and finding the best alternative system design and operation, forces businesses to use computer simulation as a tool for testing the new conditions. Since the new systems that are being built are generally more complex and costly and have less room for error due to competitive pressures, the businesses have to rely more on simulation to build the most efficiently designed and operated systems. The new systems have to be optimized in their parameters right from their beginning rather than in several months, as has been observed in semiconductor and automotive manufacturing plants.

(b) ***Cost Reduction Efforts***. The last twenty years have also been the era of lean or agile systems, especially in manufacturing and supply chain systems. Companies are forced to increase their production rates and flexibility while reducing their investments in inventories, equipment, and labor. Companies with nimble systems and lower costs have much higher shareholder value in the business marketplace. Lean systems are also more prone to variations in the product demand, lead times, unscheduled downtimes, and quality levels. In design of such systems, simulation modeling becomes an essential tool to increase the robustness of the system relative to internal and external disturbances.

(c) ***Improved Decision-Making.*** The decisions that management makes under daily dynamic conditions not under management's direct control, or management decisions that are made relative to short-term and long-term changes planned for the system, may be sub-optimal if simulation modeling is not used to test the effectiveness of each decision. Simulation modeling has been proved an effective tool in training of managers wherein they can understand the effects of their decisions on the important performance metrics of the system. The cause-and-effect relationships observable through running of the simulation models increase the effectiveness of the decision-makers. The best decisions under product mix changes, resource breakdowns, process and policy changes, schedule changes, priority changes, addition and deletion of resources, and maintenance policy changes are examples where management can gain significantly from simulation modeling.

(d) ***Effective Problem Diagnosis.*** Problem solving aids that help management solve problems such as throughput reduction, large setup times, imbalance in resource utilization, large inventories and waiting times point to simulation as the most effective tool. One can analyze the current system as well as the suggestions for improvement of the current system using simulation. The other analytical tools of operations research such as mathematical techniques, artificial intelligence, statistical techniques, and root cause analysis techniques either require too many simplistic assumptions to solve the problem or are too complex to be explained management credibly. Simulation models, especially when coupled with their animation capabilities, can solve a problem at different levels of detail and complexity with the credibility management requires for effective use in real-life situations.

(e) ***Prediction and Explanation Capabilities.*** Simulation modeling provides both prediction and explanation of a system's performance under different conditions. In addition to predicting what the system's performance will be for a set of conditions, the user can also comprehend the reasons why the system produces those results and behaves in a certain fashion through the user-defined simulated time period. Deeper understanding of the cause and effect relationships in the system also helps management formulate new or improved ideas to manage the system more effectively. In contrast to simulation modeling, other operations modeling tools are generally deficient in their explanatory capabilities and time-based evaluation of the system.

One can classify the usage of computer simulation in businesses as strategic, tactical, or operational based on the time horizon of the decisions made in the simulation study. In strategic uses, the time horizon of the decisions made in the study generally covers from three years to five or more years into the future and upper management of a company is the customer of such simulation studies. Simulation studies done for effective decision-making in new product development, product portfolio management, or new plant and warehouse construction fit this category. In tactical uses of simulation, middle management is the customer of such simulation studies and the decisions made cover one to three years into the future. Typical examples of decisions made in such studies include the purchase of new machines and equipment pertinent to an existing facility, master scheduling for maximum efficiency of resources, adding a new shift to an existing facility, the addition and/or resizing of buffers, or logistics and supply chain studies. In operational uses of simulation, the time horizon of the decisions made in such studies can be in days to weeks and months up to one year into the future. The decisions made by lower level management involving detailed scheduling of products, workforce assignments, overtime decisions, lot-sizing, and setups are typical in such studies.

The simulation models built for strategic, tactical, and operational decisions require different levels of modeling detail, decision variables, verification and validation methods, and animation. For example, a strategic level model for new product portfolio management for a Fortune 100 company may include only the new product development projects whose cost exceeds ten million dollars, represent the hundreds of tasks in the product development process as ten to fifteen major tasks in the model, use the shareholder value, return on investment, cash flow, cost of programs as the decision variables, and animate the system using dynamic time-based cost, return on investment, cash flow, and resource utilization diagrams. As a contrasting example, an operational level model for finding the optimal number of forklift trucks in a receiving and shipping department at a plant may include only those loads carried by the forklift trucks, represent the forklift truck movements with acceleration, deceleration, and maximum speed, use the truck loading and unloading times, the number of emergency deliveries due to starving stations, the number and the utilization of the forklift trucks as the decision variables, and animate the system using dynamic icons representing the forklift trucks and the delivery trucks at the docks being loaded and unloaded, static icons representing the stations where the deliveries and pick-ups are made, and dynamically changing numbers showing the inventory status of each load at each station.

3. SIMULATION WORLDVIEWS

This section describes the three fundamentally different and contrasting simulation worldviews: discrete-event, continuous, and mixed [1]. It also provides a subsidiary classification for the discrete-event worldview.

3.1. The Discrete-Event Worldview

In this worldview, time progresses in a series of steps and significant variables within the model are integer-valued. Therefore, the concept of “derivative” is inapplicable, since “discrete” in this sense is the antonym of “continuous." The number of items in a queue, for example, is inherently integer-valued. The function L(t), specifying queue length as a function of time, is constant during intervals of time and changes value at arbitrary instants of time. Its derivative is zero on the intervals and undefined at the instants of change from one integer value to another; its integral is equal to the weighted average queue length. As another example, the status of a server may be considered binary (0=idle, 1=busy) or at least integer (0=idle or starved, 1=busy, 2=blocked, 3=not in service or “down”). In this worldview, differential or difference equations are inapplicable. The discrete-event worldview applies well to study of queuing systems – and, as will become evident in Section 4, a rich variety of simulation applications can and should be viewed as queuing systems. This graph illustrates the behavior of a typical discrete variable as a function of simulated time.

Figure 1: Graph of Typical Discrete Variable as Function of Time

3.1.1 The activity-oriented approach.

In the *activity*-oriented approach to discrete-event simulation modeling, the modeler develops characterizations of each significant activity within the system under study. These characterizations describe the system changes and quantify the passage of time during each activity (e.g., awaiting service, repairing a server, or receiving service). This orientation is most conveniently employed in the context of using a general-purpose programming language to write subroutines or functions driven by a simulation engine (see Section 7). For example, the Receive_Service activity subroutine would update the busy time of the server and increment the cumulative number of items served by that server.

3.1.2. The event-oriented approach.

In the *event*-oriented approach to discrete-event simulation modeling, the modeler develops characterizations of each significant event within the system under study. Whereas activities span an interval of time, events occur at instants of time. This orientation, likewise, is most conveniently employed in the context of writing subroutines or functions to be called by a simulation engine. For example, the Completion_of_Service event subroutine, invoked at time t_0, would increment the cumulative number of items served by that server, and then examine $L(t_0)$: if $L(t_0) > 0$, decrement it by one and move one item from queue to server; else set server status to idle.

3.1.3. The process-oriented approach.

In the *process*-oriented approach to discrete-event simulation modeling, the modeler develops a characterization of how items (airplanes, customers, crankshafts, patients, mortgage applications, telephone inquiries....) flow through the system under study. This orientation is most conveniently employed in the context of using either a computer language (for example, GPSS [General Purpose System Simulator]) or a simulation package expressly designed for this use (see Section 7).

Figure 2: Comparison of Activity, Event, and Process Approaches

3.2. The Continuous Worldview

In this worldview, the system to be modeled is described in terms of differential and/or difference equations, exploiting the fact that variables of interest are continuous and differentiable functions of time. Such variables might be temperature, pressure, volume (e.g., of fluid in a tank), displacement, intensity of light, or diminution of strength. The analysis of the system then involves integration of these equations as time is driven forward. The continuous worldview is well suited for modeling of physical systems, as is regularly done in structural analysis (e.g., the compression or extension of a spring). The choice of this worldview or the discrete-event worldview may depend on the needs of the analyst. For example, consider a food-processing operation in which containers are filled with finely granulated sugar. The analyst may consider the state of the container as a discrete variable equal to zero (container not full) or one (container full). Or, the analyst may consider the amount of sugar in the container as a continuous variable ranging from 0.0 (container empty) to 1.0 (container full). When using this world view, the modeler often writes subroutines in a computer language such as Fortran or C to be driven by a simulation engine. This graph illustrates the behavior of a typical continuous variable as a function of simulated time.

Figure 3: Graph of Typical Continuous Variable as Function of Time

3.3. The Mixed Worldview

As its name implies, this worldview conflates the discrete and continuous approaches. The modeler begins by describing the system in terms of differential or difference equations, and then specifies threshold values beyond which each equation is no longer applicable. Extending the above example, the equation describing the extension of a spring as a function of time instantaneously ceases to apply when the threshold of elastic limit is crossed. The mixed worldview adapts well to modeling processes such as synthesis of chemicals or refining of oil, in which temperature, pressure, and concentration are continuous variables. Increase or decrease of these variables across thresholds may trigger events such as the startup or shutdown of a furnace, or the opening or closing of a valve. Hence, analysis should first consider the continuous aspects of the system, and then superimpose the discrete aspects, such event triggers, upon the continuous behavior. The analyst studying a system by using the mixed world view may proceed as for the continuous worldview (writing subroutines and also specifying thresholds to be monitored by a simulation engine), or may use a simulation package expressly designed to include not only both discrete and continuous modeling capabilities, but also their interaction. For further descriptions of modeling tools available, see Section 7. This graph illustrates the interaction of a continuous variable crossing a threshold and a discrete variable as a function of simulated time

Figure 4: Graph of Typical Discrete and Continuous Variable Interaction

4 AN APPLICATION ORIENTED SIMULATION METHODOLOGY

The application oriented simulation methodology suggested below has eight phases, namely:

Phase 1. Define the Problem

Phase 2. Design the Study

Phase 3. Design the Conceptual Model

Phase 4. Formulate Inputs, Assumptions, and Process Definition

Phase 5. Build, Verify, and Validate the Simulation Model

Phase 6. Experiment with the Model and Look for Opportunities for Design Of Experiments

Phase 7. Document and Present Results

Phase 8. Manage the Model Life Cycle

Each phase is described in terms of detailed steps in Table 1. Although these phases are generally applied in sequence, one may need to return to the previous phases due to changes in the scope and objectives of the study. In particular, phases 3 through 6 of the process may be repeated for each major alternative studied as part of the project.

It should be noted that the items listed for Phase 5 and Phase 7 are interpreted as guidelines rather than steps. In previous papers, Ülgen, Black, Johnsonbaugh, and Klungle [2, 3] and Ülgen, Gunal, Grajo, and Shore [4] describe each of these steps in detail. In section 6 on critical success factors, we discuss the role of some of these steps in successful execution of a simulation project.

[Insert Table 1]

5. TYPES OF APPLICATIONS

Simulation modeling has been applied in a large number of industries in solving problems in the strategic, tactical, and operational levels of management. Table 2 below lists twelve major application areas of simulation modeling with samples of issues that correspond to the different levels of management. In general, discrete-event modeling has been the most commonly applied world-view for simulation applications. It has dominated all the application areas except the Environmental and Ecological System applications; the continuous world-view is a better fit for this domain. The combined simulation world-view has been the least applied world-view due to the complexity of building models with this approach. In many cases, simulation analysts (and some of the simulation software) have preferred to make assumptions to convert the continuous component of a model to its discrete equivalent. However, this simplification can have disastrous effects on the validity of the simulation for some systems with nonlinear model components.

[Insert Table 2 Simulation Application Areas]

The first three application areas of simulation, namely; manufacturing, material handling, and warehousing and distribution systems, have been the most popular ones among simulation applications if one looks at the published material to date. In the remainder of this section we will review the applications in these areas.

5.1 Applications in Manufacturing, Material Handling, and Warehousing and Distribution Systems

The simulation applications in these three areas can further be classified into four categories based on the development stage of the design of the system in question [5]. The four categories observed in this classification are applications that belong to the conceptual design phase, detailed design phase, launching phase, and/or fully operational phase of the system. The *conceptual phase* refers to the initial stage where the new methods of manufacturing, material handling, warehousing and distribution are tested by management. Discrete-event simulation packages with three-dimensional animation capabilities are the popular simulation tools at this phase. The *detailed design phase* refers to the stage where detailed layout plans and equipment specifications are verified for the system. The principal factors considered here include equipment justifications (e.g., the number of hold tables, power and free carriers, the size of buffers), cycle-time verifications (e.g., conveyor speeds, line throughput), and line operational and scheduling issues (e.g., logic for evacuating ovens and paint booths, repairs, and product mix decisions). Discrete-event simulation packages with built-in detailed equipment features and three-dimensional animation features appear to be the most popular packages used at this stage. The *launching phase* refers to the stage where the plant operates below the designed operational conditions. In some cases it may take up to six months for the plant to operate under maximum-capacity conditions. Simulation studies performed at this stage are generally used to test operational policies (e.g., operate one of the two paint booths at a time, run each shop for one-half of the total available time, use different product mixes). Discrete-event simulation packages used at this stage do not typically require the detailed equipment features or the three-dimensional animation features. The simulation program generators with user-friendly features are the most popular packages used at this phase, as models tend to be at a macro level rather than a micro level. The *fully operational* phase refers to the stage where the plant is operating at its anticipated capacity. The simulation studies done at this phase consider product mix decisions, new product introductions, new operational policies, and line modifications. Simulation software used at this phase generally require the same capabilities as that used at the launching phase.

In what follows, we will discuss three case studies [5] belonging to manufacturing, material handling, and warehousing and distribution application areas.

5.1.1. Case Study 1: Trim and Final Assembly Line Design [5]

This simulation study was performed during the detailed design phase of a new conveyor system. An assembly plant would be making several different models of cars on one trim line. The process and flow of jobs in the system showed differences with respect to the model of cars. The conceptual design of the new system was completed following the previous version of the system. However, to accommodate the variety of the product assembly sequence, many new hardware pieces were needed. To ensure that the system could move the desired product quantities between various parts of the system, a detailed simulation model was built. An important parameter of the design was the mix of models in the target production rate. The objectives of the simulation study were:

- Verify the capability of the conveyor system to move the target number of vehicles through the trim system by considering various product mixes.

- Investigate various scenarios of assigning the size and location of empty carrier buffers by considering different product mixes.
- Analyze the impact of building a new buffer area to hold additional empty carriers.
- Determine the maximum allowable cycle times at several transfer stations by considering different product mixes.

Some of the important assumptions of the study were as follows:

- All manual operations can be completed within the given cycle time.
- All materials are always present.
- The line speed would be set higher than the required rate so that occasional downtimes could be tolerated.
- There are three models of cars and eight possible mixes of those models.

The system consisted of a chassis buildup system, an engine delivery system, a frame buildup system, and a final trim line. All material movement were made by using power and free conveyors except for the frame buildup area where a chain conveyor was used to move the units continuously. The transfer of units and subassemblies between major areas required complicated equipment that was prone to mechanical failure. Since there was limited room for buffers, an additional storage space was designed at the mezzanine level. The size of the buffer was being questioned since there were random downtimes at major transfer points. Since there were no detailed data, the system was designed to run at a speed 12% higher than the speed required, to allow time for breakdowns and shift breaks. However, the designers wanted to confirm that the system would be capable of delivering an average number of vehicles to meet the weekly production target at a 5 to

10% downtime rate. Based on past data, only an average recovery time of 5 minutes was specified. Also, the newly designed engine assembly area required the proper number of pallets in the system to support the production of all different types of jobs. Since there could be a variety of job mixes to be produced in the system, it was necessary to determine a number of pallets that would work with all possible product mixes.

During the simulation study, first an evaluation of possible product mixes was made using a baseline layout. This portion of the study helped to determine the maximum allowable cycle times at critical stations to accommodate a variety of product mixes. Then the study focused on evaluation of the size of the empty carrier buffer. Three different layout alternatives were investigated. The simulation runs indicated that there would be no difference between layouts with respect to the average throughput capability. However, the utilization of various subsystems would be greatly affected by allocation of the empty carriers. Table 3 depicts, for all three layout alternatives, the time required to starve various subsystems after a catastrophic breakdown at one of the critical stations. The table clearly demonstrates that the first layout alternative is significantly better than the latter two in protecting the chassis buildup system against long periods of breakdowns.

[Insert Table 3 here—Time to Starve Subsystems After Breakdown]

The model showed that at the transfer point from the engine build line to the engine deck area, the control logic and buffer size originally proposed would not support the cycle-time requirement of the engine assembly area. Also, the simulation showed that the final assembly line would be starved immediately if the downtime at the body assembly area were longer than 3 minutes. It was also determined that the buffer storage space placed in the mezzanine level would be sufficient only for breakdowns of relatively short duration. An evaluation of an alternative design showed that additional empty carrier lanes were required to support the system for a longer time should downtime occur at a body assembly point.

5.1.2. Case Study 2: Paint Shop Material Handling and Model Mix Scheduling [5]

This study involved simulation modeling and analysis of a paint shop and an adjoining automated storage and retrieval system (AS/RS) during the conceptual and detailed design phases. In addition to evaluating the design, the animation of the model was used as a visual tool to facilitate the brainstorming sessions of the design team. The objectives of this study were as follows:

During the Conceptual Design Phase:

- Evaluate the conceptual design at each iteration of the design cycle to determine the potential bottlenecks and identify alternative solution strategies.

During the Detailed Design Phase:

- Determine the throughput capability of the system.
- Assess the feasibility of the proposed shift schedules and paint booth strip sequences.
- Investigate the best stock levels of various products in the AS/RS.
- Analyze the impact of different trim line operation schedules on the number of out-of-sequence conditions.

The system consisted of the following subsystems in sequence: (1) electrocoat and phosphate, (2) sealer lines and sealer gel oven, (3) prime booth and prime oven, (4) main enamel booth and enamel oven, (5) inspection lines, (6) spot repair area, (7) second-coat paint booth and oven, (8) paper masking and repair lines, and (9) the AS/RS (see Figure 5). The material handling equipment in the system consisted of many two- and three-strand chain conveyors, lift tables, turntables, and power roll beds.

Layout of Paint Shop and Adjoining Automated Storage and Retrieval System
Insert Figure 5 here

The following parameters and variables (evaluated in what-if scenarios) were used in the simulation model: (1) conveyor speeds, spacing, and speed-up section data; (2) cycle times at repair and mask lines; (3) cycle times at spot repair area; (4) product and paint mixes; and (5) major and minor repair percentages.

The model also required a front-end scheduling routine that was customized using a programming language (e.g., FORTRAN and C). Because some of the units required several passes through paint booths, they took a longer time to be ready for delivery to the trim lines. However, since the product mix showed significant differences between shifts, and since the trim lines operated on a different shift pattern, the jobs that required long processing times were pulled ahead of their original sequence. Thus even though they would be taking more time than the other jobs, by the time they were completed, they would be able to catch their original position in the assembly sequence. Because of the randomness of the defect rate, there would be a good chance that some units would miss their sequence if they were not moved sufficiently ahead in the paint sequence. On the contrary, if they were moved too much ahead of their sequence, they would finish the paint process much earlier than the rest of the units. Therefore, to protect against such random variations in the makespan of different job types, a buffer storage bank was held in the adjoining AS/RS. This buffer would be sized to allow sufficient time for all units to catch their original sequence. The following are some of the original rules for resequencing the jobs:

- Jobs with two colors were moved ahead by 100 jobs for two product types.
- Jobs with three colors were moved ahead by 200 jobs for only one of the models.
- Pattern color jobs were moved ahead by 200 jobs.
- A job with more than one matching criterion was moved ahead by the sum of the jobs required by each criterion (e.g., a two-color job with patterns was moved ahead by 400 jobs).

Some of the model assumptions were as follows:

- Two vehicle models, A and B, are considered. Model A vehicles have up to two coats of paint, whereas model B vehicles have up to three coats of paint.
- The model mix was known and assumed constant within a day.
- The major repair percentage is 22% and the minor repair percentage is 9% on average with random occurrences.
- Minor repair times are randomly distributed between 30 and 120 minutes and are performed at a dedicated area. Major repairs go through the second paint loop as necessary.

- Shift patterns are known and constant. The first shift is dedicated to model B and the second shift is dedicated to model A at the paint shop. The trim shop runs only one shift and makes both products.
- All conveyors run at full speed with negligible downtimes.

Analysis of the model involved an evaluation of the alternative job sequencing policies to choose one that will eliminate late jobs at the trim lines for all job types. In addition to sequencing concerns, the model was used to investigate the selectivity system (AS/RS) utilization. The runs of the model indicated that there was no reason to

[Insert Table 4 here—Results of Investigation]

resequence model B vehicles since the plant was planning to store a full day's worth of buffer in the AS/RS for this type. The model showed that during the second shift in the paint shop all of the longest paint jobs would be completed for the next day's production at the trim lines. Results from some of the scenarios investigated are summarized in Table 4 for model A only. The table depicts the results with and without resequencing. In either case, different levels of model A buffer in AS/RS were tested to find a level that will balance the buffer size and the number of missed jobs. The results in the table indicate that a buffer size of 180 vehicles would be sufficient to avoid the missing jobs for the vehicle model A. It was also determined that with chosen buffer sizes, the utilization of the AS/RS was at a feasible level. The plant would make substantial cost savings by avoiding the reprogramming of their production monitoring system for vehicle model B.

5.1.3. Case Study 3: Warehousing Study [5]

This project studied the proposed changes to a warehouse and the proposed material handling equipment. The modifications to the system were needed as a result of increased storage, shipping, and receiving volumes anticipated due to packaging changes in existing products and introduction of new product lines. It was desired to determine alternative ways of increasing both cubic storage space and material handling (shipping and receiving) capabilities. The challenge was to optimize the layout of the warehouse and select the most suitable material handling equipment to provide adequate service based on planned future volumes.

The goals of the study were to identify system constraints that could limit future space and handling requirements and to suggest potential improvements and modifications to the system design. The design alternatives were based on the following system parameters: (1) dedicated versus random storage rules, (2) original rack orientation versus rotated (perpendicular to the docks) orientation, (3) aisle width and overall storage space utilization, and (4) capacity of material handling equipment, most notably the number of lift trucks.

The results from the simulation model demonstrated that: (1) randomized storage was better suited to this situation than dedicated storage, (2) the rotated orientation with the corresponding narrower aisle configuration resulted in an 85.96% increase in overall unit load storage capacity, (3) the rotated orientation also resulted in an increase from 23.57% to 41.95% in total storage space utilization, and (4) the existing number of lift trucks was sufficient to service the increased volumes.

6. CRITICAL SUCCESS FACTORS

The proper introduction of simulation into a company or business unit within a company begins by gaining management understanding and support, not by training at a technical level. Managers not already acquainted with simulation should first be reminded of the business motivations for using it (see Section 2) and then provided with an overview of how simulation works, what it can accomplish when properly used, what its limitations are, and the type and scope of investment required as a prerequisite to obtaining benefits from simulation. Serious errors to avoid are overselling the benefits or understating the investments in personnel, training, time, data collection, and software required to obtain those benefits. Valuable resources for the introduction of this technology are benchmarks of companies using simulation, overview seminars, attendance at simulation conferences which provide non-technical tutorial tracks, and non-technical books on simulation such as [6] and [7]. After tentative acceptance of simulation – that is, a willingness to "try it out" or "give it a test drive" – has been achieved, an initial simulation project should be specified and staffed. Very importantly, this project should be *small* and of sharply defined scope and objectives, so that managers will be able to recognize success when it has been achieved. As examples (compare with types of applications in Section 5), simulate one workcell, not one production department; simulate one restaurant, not all six in the city; simulate one baggage claim area, not the whole airport terminal; simulate one ward, not the fifth floor of the hospital.

When staffing a simulation project, industrial engineers are the “simulation champions” of choice, due to their experience in assuming a holistic process viewpoint, training in simulation – hence awareness of its capabilities and limitations, knowledge of mathematics and statistics, and extensive experience serving as a communication conduit between managers and production workers and their supervisors. Successful simulation requires a suite of skills in addition to model building: statistical analysis, oral and written communication, interpersonal diplomacy, and, most fundamentally, a thorough understanding of the current or proposed production system to be modeled and analyzed. Particularly when a company is beginning use of simulation, the model building skill and the system understanding are likely to repose in two different people, underscoring the importance of communication skills on the part of the model builder/simulation analyst. The simulation analyst must be able to enlist the process expert’s co-operation while developing understanding of the process, gathering data, and later presenting results and recommendations emerging from the study.

When the first success of simulation whets managers’ appetites for further use of simulation, these managers should establish a project discipline. A "road-tested" template for this discipline comprises eight phases (see Section 4). Notice that much "up front" work is necessary before actual modeling begins. As the above project discipline indicates, by the time model construction begins, answers to many questions have been determined. Several of these questions and example answers are:

Question: What system is to be modeled?

Example answer: Department B will be included in the model; upstream department A and downstream departments C and D will not be included in the model.

Example answer: Departments B and C will be included in the model; upstream department A and downstream department D will not be included in the model.

Question: What answers will the model provide?

Example answer: The model will predict the maximum number of jobs per hour attainable by adjusting buffer sizes while leaving conveyor speeds unchanged.

Example answer: The model will specify the maximum number of jobs per hour attainable by adjusting conveyor speeds while leaving buffer sizes unchanged.

Question: What modeling strategies will be used?

Example answer: The frequent supply of raw material in small batches to a department will be treated as a continuous stream.

Example answer: The five machining steps of Operation 30 will be treated as one process, not subdivided.

Question: On what assumptions will the study be based?

Example answer: If a given piece of equipment breaks down, repair can always begin at once.

Example answer: Supply of raw material will never be exhausted.

To the uninitiated, model construction, very probably using unfamiliar software, seems the most daunting and time-consuming step. Veterans of simulation studies are well aware that data collection usually requires considerably more time. Verification of the model is akin to debugging – confirming that the model functions as the modeler intends.

Validation of the model confirms that the model is an accurate representation of the current or proposed system relative to all performance metrics to be assessed by management.

Figure 6: Relationship Between Model Verification and Validation

Experimentation with the model, to learn more about the system under study, deserves a generous allotment of time; it is during this step that management receives a return on the investment in training, software, and time required to gather data and to build, verify, and validate the model. Statistical expertise is most essential during data collection (to incorporate statistically valid characterizations of stochastic data within the model) and during experimentation and analysis (to assess performance of candidate systems). Simulation studies, like any scientific inquiry, raise questions as well as answering them – after all, industrial engineers seek not just improvement, but *continuous* improvement! Therefore, documentation, both internal to the model and external (reports, project logbooks), is vital to enabling subsequent analyses to build on the work already accomplished instead of redoing it.

More administratively and strategically, managers should anticipate the problem of how to accommodate additional demand for simulation spawned by its initial success (a good problem to have). Will this demand be met internally or externally? Meeting it internally entails the assemblage of a staff of experts, by hiring them and/or providing appropriate training to current personnel. Meeting it externally requires establishment of a long-term, high-trust relationship with a qualified vendor of simulation and analysis service. Training in-house process experts (e.g., production supervisors) to use simulation has the strong appeal of making the process expert and the simulation model builder one and the same – surely easing and enhancing the communication between them! In-house seminars and the establishment of an intracompany simulation users' group work well to not only publicize simulation as a value-adding technology, but also to disseminate knowledge of its proper praxis. Therefore, the initial simulation analysts should gradually migrate from the role of "constructing models to order" to the role of enabling colleagues to construct and analyze models. Recent advances in the intuitive usability of simulation tools (see Section 7) have increased the plausibility of this choice. Even then, a relationship with a qualified vendor of simulation service should be on standby to handle urgent needs. This vendor should be a disinterested specialist in simulation modeling and analysis, not a vendor of production equipment or systems – the latter choice is akin to assigning the cat the guardianship of the canary.

7. OVERVIEW OF TOOLS AVAILABLE

The extensive array of analytical tools available for simulation analyses can conveniently, although imprecisely, be grouped into four categories: general purpose languages, simulation languages, simulation packages (simulators), and tool suites. Table 5 below lists the software that can be categorized into these four classes. More information on each software tool can be found in the *Proceedings of the Winter Simulation Conference,* published annually by a consortium of technical societies including, for example, the Institute of Industrial Engineers.

[Insert Table 5 here—A Classification of Simulation Software Tools]

General purpose programming languages amenable to mathematical expression, such as Fortran and C, have long been used for simulation. Using these languages, an expert can describe extremely complex, idiosyncratic systems to whatever level of detail may be appropriate relative to study objectives, time available, and budget available. The use of a general-purpose language becomes much more efficient and effective when a simulation engine is available for tasks common to all simulations, such as maintenance of the simulation clock and of calendars of current and scheduled events within the model. In this situation, the analyst writes subroutines or functions which the simulation engine calls at appropriate times.

Other programming languages have been developed expressly for simulation modeling. Two of the most venerable and most widely known are GPSS [General Purpose System Simulator] and SIMSCRIPT. GPSS supports discrete-event simulation, but does not support the continuous or the mixed worldviews. Since GPSS is a block-structured language, whose blocks represent processes such as joining a queue, beginning to use a resource, or freeing a resource, it is particularly well-suited to the process approach. SIMSCRIPT, a more complex and powerful language, supports the discrete, continuous, and mixed worldviews, partly because the elements of SIMSCRIPT are less explicitly linked to real-world elements than are those of GPSS.

Simulation languages are being rapidly and largely supplanted by simulation packages. Use of these packages greatly reduces (but does not eliminate) the writing of computer code. When using a simulation package, the user builds the model primarily with the mouse, using predefined constructs such as "machine," "resource," "conveyor," or "buffer." Process logic is then provided to the model via an English-like programming language, as shown in this generic example:

```
IF Utilization(resource_1) < Utilization(resource-2)
    THEN USE resource_1 for 2.5 minutes
    ELSE USE resource_2 for 3.5 minutes
END IF
```

Use of a simulation package shortens the model building, verification, and validation phase (the fifth phase in the project discipline recommended in Section 6). Furthermore, use of a simulation package instead of a simulation language typically permits concurrent construction of a model and its animation.

Currently, simulation packages are evolving and coalescing into tool suites (see Section 7). For example, many simulation packages now include statistical capabilities to fit probability densities to empirical data, construct confidence intervals for system performance metrics, and undertake design-of-experiments calculations. High quality packages readily interface with spreadsheets and data base software. A worthy conceptual goal to be kept in mind by the analyst when choosing software tools is "Will I ever have to read an output number from one software tool so I can key it into another software tool as input?" Surely the desired answer to this question is "No"!

8. INTEGRATION WITH RELATED ANALYTICAL METHODS AND TOOLS

During the last ten years, there had been significant progress in the integration of simulation tools with other analytical tools. Table 5 lists some of the software suites and suite components. The most significant among these has been the integration of discrete-event simulation tools with the ergonomics and robotics simulation tools that are based on the continuous simulation worldview. The toolset of Quest+IGRIP+Ergo by Deneb Corporation is one such example. The simulation analyst can develop a discrete-event model in Quest which may incorporate a robotic cell model developed in IGRIP as well as an ergonomic model of a human operating an assembly machine developed in Ergo. Many toolsets are tightly coupled while others can be combined with other software relatively easily. One such toolset component is the Optquest optimization software, which couples with a number of simulation software tools such as ARENA and WITNESS. On the other hand, the statistical input analyzers such as ExpertFit and Stat::Fit can easily be used by any simulation software since they needn't be tightly coupled with them.

[Insert Table 6 here—Simulation Tool Suite Components]

Simulation engines also have been used in scheduling software for many years in its deterministic form. Scheduling software such as AutoSched and Tempo perform their forward scheduling plans based on deterministic scheduling of events into the future. A more recent use of the simulation engines has been in the Business Process Reengineering

(BPR) tools. For example, ARIS, a BPR tool incorporates a simulation engine to compare the performance of the current and future processes before new processes are implemented in a system.

9. FUTURE TRENDS

Simulation software tools will continue their integration with other tools to form tool suites. These other tools may be spreadsheets, statistical analysis software, mathematical optimizers, programmable logic designers, ergonomic analysis software, or process flow layout and analysis tools. Increasing understanding and prevalence of object-oriented software design and programming methods significantly assists the integration of traditionally free-standing simulation tools with these correlative analytical tools.

Spurred in large measure by the increasing power and ease of use of simulation tools (see Section 7), simulation is achieving not only more frequent use, but more widely based use. Not so many years ago, simulation studies were the province of highly specialized experts in simulation-specific computer languages; therefore, these studies were reserved for special occasions. Whereas work was brought from its place of origin to mainframe computers, personal computers and their software readily go to the work. Simulation analysis will continue to follow this path. Increasingly, a simulation study will routinely be spawned by capital expenditure proposals, anticipated change in demand mix, suggestions of change in operational policy, or challenges to scheduling methods. As simulation increases its penetration within organizations, the simulation model builders will increasingly be the end users of the simulation results.

Also, the use of Internet-based (web-based) simulation will increase, especially for large, complex models. Web-based simulation is highly attractive for such models, which characteristically make heavy demands upon computer resources. Expert modelers can subdivide process logic within such models to enable multiple processors to undertake computational work concurrently. After that subdivision has been verified logically correct, the Internet provides an infrastructure for distributed processing.

Another significant trend in simulation is its increased use all along supply chains, in contrast to use within one company at a time. A supply chain, like any other chain, is no stronger than its weakest link. The benefits of long-term trust-based relationships with suppliers and vendors, compared to short-term price-based relationships, are rapidly becoming more conspicuous and more widely understood. Furthermore, it is no longer economically or operationally feasible to hide potential problems under a thick layer of inventory. Both these trends, in concert with the increasing ease of use of simulation software, will continue to increase the number of simulation studies whose scope extends far beyond the walls of one company.

The previous trend is one of several reasons that simulation is being applied to the analysis of larger and more complex systems. Increased use of parallel and distributed simulation, made possible by both hardware and software advances, will meet the escalating demands for computational power made by these large, complex simulation models.

10. SUMMARY AND CONCLUSIONS

Simulation analysis methods have high power and value, in the sense of business justification. The applicability of simulation, using an appropriate worldview, is extremely broad. Successful use of simulation is contingent upon its proper introduction into a company, the establishment of and adherence to a well-defined and disciplined methodology, and the selection and proper usage of appropriate software tools. Furthermore, simulation analyses are capable of working synergistically with other analytical methods toward goals of process improvements and increased efficiency.

AUTHOR BIOGRAPHIES

Onur M. Ülgen is the President of Production Modeling Corporation (PMC), a Detroit, Michigan, USA-based productivity improvement services company, as well as a Professor of Industrial and Manufacturing Systems Engineering at the University of Michigan-Dearborn. He received his Ph.D. degree in Industrial Engineering from Texas Tech University in 1979. His present consulting and research interests include simulators applications, scheduling, layout optimization, project management, and modeling of integrated information systems.. Dr. Ülgen is a member of IIE, INFORMS, SCS, PMI, and APICS. He has been a consultant to major international companies including General Motors Corporation, Ford Motor Company, Daimler-Chrysler Corporation, Aeroquip, National Steel, and Whirlpool.

Edward J. Williams holds bachelor's and master's degrees in mathematics (Michigan State University, 1967; University of Wisconsin, 1968). From 1969 to 1971, he did statistical programming and analysis of biomedical data at Walter Reed Army Hospital,

Washington, D.C. He joined Ford in 1972, where he works as a computer software analyst supporting statistical and simulation software. Since 1980, he has taught evening classes at the University of Michigan, including undergraduate and graduate statistics classes and undergraduate and graduate simulation classes using GPSS/H®, SLAM II®, SIMAN®, or ProModel®. He is a member of the Association for Computing [ACM] and its Special Interest Group in Simulation [SIGSIM], the Institute of Electrical and Electronics Engineers [IEEE], the Institute of Industrial Engineers [IIE], the Society for Computer Simulation [SCS], the Society of Manufacturing Engineers [SME], and the American Statistical Association [ASA]. He serves on the editorial board of the *International Journal of Industrial Engineering – Applications and Practice*.

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FIGURE CAPTION LIST

ILLUSTRATIONS

None.

TABLE LIST

TABLES