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PERFORMANCE EXCELLENCE
IN THE WOOD PRODUCTS INDUSTRY

OPERATIONS RESEARCH

Simulating a Manufacturing System: An Introduction

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Discrete event simulation is a powerful tool to help understand and manage complex manufacturing systems such as those found in the forest products industry. A system is defined as a collection of entities, usually people and machines, that act and interact toward the accomplishment of some logical end (Law and Kelton 1991).

Simulation is a powerful analytical tool for designing or experimenting with complex systems. Simulation has been defined as the process of designing a model of a real system and conducting experiments with this model either to understand the system's behavior or to evaluate various strategies for operating it (Pegden et al. 1995). When we talk about real systems, we make the distinction between the real system (existing or planned) and the simulation model of the real system.

Simulation is an important tool when the risk involved with modeling is low compared to trial and error with the real system. For example, suppose a new piece of machinery is going to be inserted into an established production line. Management can buy the new machine and put it into production, checking later to see whether the new machine actually does increase productivity, variety, quality, or whatever the goals were

Operations research (OR) is concerned with scientifically deciding how to best design and operate people–machine systems, usually under conditions requiring the allocation of scarce resources.[1]

This publication, one of a series, is offered to supervisors, lead people, middle managers, and anyone who has responsibility for operations planning in manufacturing facilities or corporate planning over multiple facilities. Practical examples are geared to the wood products industry, although managers and planners in other industries can learn OR techniques through this series.

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One of the most powerful features… of simulation is its ability to model random behavior or variation.

and, of course, increase the profit. If the system with the new machine does not meet the goals established, then management could remove the machine and lay off the employees hired to operate it.

A better approach begins with collecting data on current mill operations. Some data probably are already available; e.g., on the mix of products flowing through the mill, the grade or specification of different products, machine cycle times, and downtime for individual pieces of equipment.

Historical data can be very important and can greatly shorten the duration of data collection for simulations. One note of caution: historical data are valid only if nothing has changed in either the operations or the material mix as products flow through the manufacturing process. If you replaced most of the primary breakdown equipment 6 months ago in the green end of the sawmill, then data more than 6 months old won't reflect the new—and hopefully improved—process.

Using the collected historical data, we construct theoretical probability distributions to model the proposed new machine processes; then, we insert this into our model of the current system. (In a later publication, we will talk about how to choose the best probability distributions to model your processes.)

By running the model, we can observe the impact of the proposed new machine on the overall manufacturing system. If the machine works well in the modeled system, we can with some confidence believe that the actual machine would work well in the actual manufacturing system. But, if the proposed machine causes much disruption in the model, then we also can expect that the real machine would disrupt the real system. Based on this information, management can make decisions without disrupting the actual system—without removing a real machine or laying off employees.

Use simulation when:

- Experimentation with the real system is infeasible, disruptive, and/or too expensive
- Other mathematical or analytical methods won't work
- You need to examine systems as they would operate over a given time frame
- You want to compare alternative proposed system designs, or alternative operating policies for a single system, to see which best meets the specified requirements

Simulation Model Characteristics

Simulation models are:

- Static or dynamic, and
- Deterministic or stochastic, and
- Continuous or discrete

Static and Dynamic Simulations

A static model represents a system at a particular time. One of the most common types of static simulation, Monte Carlo simulation, uses random numbers to solve (usually) stochastic problems, and the passage of time plays no role. The object is to repeatedly reconstruct the situation in variant forms, based on events and values that turn up each time.

A dynamic simulation model represents a system as it evolves over time; for example, simulating a computer-numerically-controlled (CNC) router for a 40-hour work week (Law and Kelton 1991).

Deterministic and Stochastic Simulations

A deterministic simulation model assumes no variability in model parameters and, therefore, contains no random variables. If a deterministic model is run with the same input values, it will always calculate the same output values. Examples of deterministic simulation models developed for the forest products industry are LUMGRAFS, for examining the financial feasibility of producing different proprietary grades (Reeb and Massey 1996), and ROMI-RIP, for examining processing scenarios in rough mills (Gatchell et al. 1999). Howard (1988) used a deterministic simulation model to estimate profits from sawing competitively bid timber.

Deterministic simulation models obviously can be useful. However, most manufacturing processes have random or unpredictable variables in their environment or components; then, stochastic modeling is used to simulate the system in question (Harrell et al. 2000, Pegden et al. 1995, Law and Kelton 1991, Pritsker 1986, Shannon 1975). One of the most powerful features of simulation is its ability to model random behavior or variation. Interdependencies and variability, or chance, characterize almost all human-made systems: operation times, machine cycles, reject rates, arrival times, downtimes, employee activities, etc. These characteristics make complex systems difficult to study, analyze, and predict (Harrell et al. 2000).

A stochastic simulation model contains one or more random variables to describe processes in the system being studied. This is an important point to remember because output data of a stochastic simulation are themselves random and therefore only *estimates* of the true characteristics of the model. Using a deterministic model, the result of a single simulation run is an exact measure of the performance of the model, but using a stochastic simulation, multiple runs are necessary, and even then the results measured across those replications provide only an estimate of the expected performance of the model and system being studied. We will discuss this in much more detail in a later publication in this series.

Continuous and Discrete Simulations

Most manufacturing systems...
are modeled as dynamic and discrete event simulations.

In a continuous simulation, state variables change continuously. For example, in the flow of a liquid through a pipe, flow of water through a canal, or flight of an airplane, the state variables of position and velocity change continuously with respect to each other. During a discrete simulation, state variables change only at a countable (or finite) number of points in time. For example, grading lumber in a sawmill is discrete. The number of graded boards changes only after a board reaches a grader and is graded, trimmed, and sorted.

Most manufacturing systems are modeled as dynamic and discrete event simulations. Most are stochastic in nature and use random variables to model interarrival times,* queues, processes, etc.

The manufacturing sector increasingly uses discrete event simulation in a wide variety of industries including automotive (Jayaraman and Gunal 1997), military (Hill et al. 2001), and electronics (Farahmand 2000).

Discrete event simulations are used to analyze overall manufacturing environments, specific issues, and individual measures of performance. Manufacturing environments that can be studied include adding new equipment, upgrading existing machines, changing factory layout, or building a new factory area. Each of those changes will lead to changes in certain measures of performance for the system. Examples of measures of performance are work-in-process, part lead times, part throughput, and machine utilization.

In manufacturing environments it is important for managers and engineers to get a systemwide view of the effect local changes will

* Interarrival time is the interval between the points in time at which items arrive at a certain location.

have on the system. If a change is made at a particular location, its impact on the process at this location may be fairly predictable, but without simulation it may be impossible to determine the impact of the change on the performance of the overall system (Law and Kelton 1991). For example, a bottleneck at a machine center causes too much work-in-process inventory to accumulate at this location. The boss decides to add another machine to eliminate the bottleneck. However, that additional machine's throughput will have an impact on processes that follow. In many cases, new bottlenecks will occur at downstream processes that were either balanced or waiting for product before the new machine was installed. Simulation is a way to look at all the changes and their effects on the system without disrupting the current system.

Here is another example of the importance of taking a systems view. In a manufacturing cell at an Oregon firm, the output of eight shaping machines flowed downstream to a single boring and sanding machine which, not surprisingly, was the bottleneck for the cell. The simulation model evaluated "obvious" solutions: add a second boring and sanding machine or a third shift on the single machine. However, the simulation found that neither greatly improved throughput. It turned out that the primary cause of the bottleneck was not equipment limitations but the fact that standard procedures called for the operator to grade product before loading the machine. Although grading was very fast, a simulation that had the cell using offline grading (i.e., while the machine was running, or grading done by another operator) resulted in far greater throughput than the far more expensive options of adding a second machine or a third shift.

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Simulations in the Forest Products Industry

Simulations have been used in the forest products industry to help improve all aspects of a company, from production to marketing (de Kluyver and McNally 1980). Simulations have been used to study various veneer slicing procedures (Schmoldt et al. 1996), furniture mill operations (Kyle and Ludka 2000, Wiedenbeck 1992), and sawmill processes (Adams 1984 and 1988, Aune 1974, Hall and Jewett 1988, Kempthorne 1978, Kline et al. 1992, Lin et al. 1995, Pennick 1969, Reeb 2003, Stiess 1997, Wagner et al. 1989, Wagner and Taylor 1983). These simulation models were developed using general-purpose programming languages or special-purpose simulation languages.

Good simulation software…
will contain good statistical capabilities so that sources of system randomness can be modeled using theoretical probability distributions.

General-purpose Languages, Special-purpose Simulation Languages, and Simulators

Simulation models are programmed using general-purpose computer languages, special-purpose simulation languages, and simulators.

General-purpose computer languages, such as FORTRAN, C, BASIC, and PASCAL, are designed to solve a broad class of problems, not just simulations (Harrell et al. 2000, Shannon 1975). General-purpose languages were the first computer languages used to develop simulation models. Advanced programming skills in a specific language, and a lot of time, are necessary to develop simulations that can model complex manufacturing systems. The models often are unique to the system being modeled, so when a new simulation model is started, much of the earlier model cannot be used.

Special-purpose simulation languages, such as SLAM, SIMAN, and GPSS, have characteristics that make them more convenient—i.e., they require less programming—to use for simulating systems (Pegden et al. 1995, Stahl 1990, Pritsker 1986). They are designed to solve a particular class or type of problem (Shannon 1975). They can be general in nature but have special features for specific types of applications. For example, SLAM II has manufacturing modules for conveyors and automated guided vehicles. Special-purpose simulation languages are designed so the user can model almost any type of system regardless of its operating procedures or control logic. Random number generation, ability to call and use different probability distributions, modeling elements, and other characteristics make simulation languages ideal for modeling systems.

Simulators are a relatively new type of simulation software that allows one to simulate a system with little or no programming. The simulated system is built using a graphical interface with drop-down menus and icons.

An advantage of using a simulator instead of a simulation language is that developing the model can take considerably less time. A disadvantage of using some simulators is their limited ability: they can model only those system configurations allowed by their standard features. Other simulators allow the user to write commands to model complex decision logic while still using menus and graphics to develop most of the model (Law and Kelton 1991).

Another advantage to simulators is that those not familiar with simulation but familiar with the system being studied can look at the animated model and help validate how well the model mimics the real system. Many special-purpose simulation languages also employ an animation package that can greatly help in verifying (ensuring that the model behaves the way the modeler intended) and validating (ensuring that the model is a true representation of the system being modeled) simulation models.

Good simulation software will contain good statistical capabilities so that sources of system randomness (interarrival times, processing times, downtimes, etc.) can be modeled using theoretical probability distributions. The software will contain a wide variety of standard distributions from which to choose and a multiple-stream pseudorandom number generator.* In addition, you should be able to make independent replications of the model automatically, using different pseudorandom numbers but starting in the same initial state each time. You should be able to specify a warmup period, and the software should have the statistical abilities to measure performance. These topics will be covered in more detail in later publications in this series.

Table 1. Preferred tools of simulation modelers

Type of language	Users preferring (%)
General-purpose languages	
C	28
FORTRAN	27
PASCAL	7
BASIC	6
LISP	4
Other	10
None	18
General-purpose simulation languages	
SLAM II	28
SIMAN	28
GPSS	11
SIMSCRIPT	6
Other	11
None	16
Special-purpose simulators	
PROMODEL	14
SIMFACTORY	8
FACTOR	4
WITNESS	2
Other	12
None	60

In a 1995 survey (Cochran et al.), modelers were asked what type of simulation programs they most often used (Table 1).

*We call these numbers pseudorandom because they behave as random numbers but in fact are not. The pseudorandom number generator produces a flow of numbers that are samples (observations, draws, or realizations) from a continuous, uniform distribution between 0 and 1 and are independent from one another. All other observations from other probability distributions that drive simulations start with random numbers. If you wish to experiment with the simulation, you must be able to replicate those same numbers; therefore, they are not truly random. We will spend more time talking about this in a later publication when we discuss how to use other probability distributions to drive your simulation models.

Any of the three types of software has pluses and minuses. Most simulation software companies offer a free or relatively inexpensive demonstration ("demo") version of their product. However, the demo version typically is limited in the size of the model you can construct with it. Try out several of these before deciding what type of simulation software to purchase. Most industrial versions of simulation software cost thousands of dollars, so make sure you are comfortable with a product before purchasing it.

Table 2. Major uses for simulation in various U.S. industries

Project goal	Approximate percentage of simulation studies
Design (facility design, system development)	22
Research (product development, industry modeling)	21
Scheduling (work-flow analysis, priorities, due dates)	19
Planning (forecasting, analysis of market strategies, predict consumer behavior)	17
Assignments and allocations (personnel analysis and scheduling, resource allocation)	17
Other (e.g., testing scientific theory, studying health care systems, modeling weapon systems, analyzing data)	4

Uses

Simulation studies are used for many types of activity. The Cochran et al. survey examined the major uses for simulation in various industries in the United States (Table 2).

Simulation studies can be expensive. Data collection and model formulation can be very time consuming, depending on the complexity of the system being studied.

However, without good, representative data and good problem formulation, you could make erroneous (and expensive) conclusions about the system being studied. The Cochran et al. survey examined the time it took to complete simulation studies for various industries (Table 3). On average, 76 percent of the simulation studies took more than 1 month to complete; 29 percent of the studies took more than 6 months to complete.

Time spent on simulation studies has been broken into several categories: formulating the problem, collecting and analyzing current and historical data, developing computer models, and implementing solutions. Surveys in 1970 and 1995 showed most of the time was spent on developing the computer model (Table 4). Maybe this shouldn't surprise us,

Table 3. Time to complete a simulation experiment

	Less than 1 week	1 week to 1 month	1 to 3 months	3 to 6 months	More than 6 months
Minimum time	49%	25%	13%	6%	7%
Average time	4%	20%	31%	16%	29%
Maximum time	0%	4%	15%	16%	65%

since most simulation modelers are probably computer science or engineering majors who enjoy working with computers.

You should expect to spend 45 to 50 percent of your time on problem formulation and on collecting and analyzing empirical and historical data, and you should spend at least 25 percent of the time implementing the results. With high-speed, cheap computing and sophisticated simulation software, you should be spending less than a third of the time developing the computer model. We believe the reason respondents to the 1995 survey spent 55 percent of the time developing computer models is that they are comfortable with and enjoy working with computers.

Table 4. Time spent on phases of simulation studies

	Percentage of total project time		
Phase	Actual 1970[1]	Actual 1995[2]	Recommended[3]
Formulating the problem	25	14	25
Collecting and analyzing data	25	15	20
Developing the computer model	40	55	30
Implementing solutions	10	16	25

[1] Gershefski 1970
[2] Several categories are combined (Cochran et al. 1995)
[3] Shannon 1975.

Shannon (1975) noted that only a very small percent of project time was spent implementing the findings. He argued that if the study was important enough to do, then it was important to spend more time on interpreting and implementing the results. Even today, simulation is too often thought of, by those responsible for modeling, as a computer problem rather than as a tool for creating and implementing solutions for real-world problems.

Projects initially can cost more when using simulation, especially during the design phase of the project (Harrell et al. 2000). However, the overall cost of the project often can be less because the costs of implementation and operation are less when simulation is used (Figure 1).

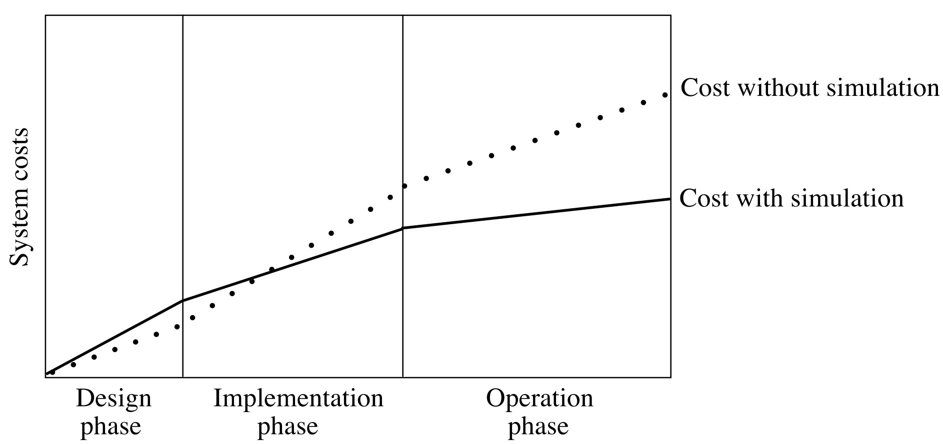

Figure 1. Comparison of cumulative system costs with and without simulation (Harrell et al. 2000).

A Summary and a Look Ahead

Simulation is one of the most used operations research (OR) methods in the world. This overview of simulation hopefully gave the reader some idea why it is considered such an important tool for many businesses. It's not just computer programming.

Future reports in this series will discuss:

- **Data collection** Often, during the data collection or early modeling stages, much useful information about the system is uncovered—sometimes making it unnecessary to complete the computer programming phase of the study.
- **Teamwork** It takes teamwork from the operators through upper management to assure that complex simulation studies succeed.
- **Analysis and implementation** Ravindran et al. (1987) describe simulation as one of the easiest tools of management science to use but probably one of the most difficult to apply correctly and perhaps the most difficult from which to draw accurate conclusions.

In later publications, we will discuss how to work through some of these difficulties, and we'll discover how useful simulation can be to those in forest products manufacturing.

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