CAN STOCHASTIC MODELING HELP YOU MAKE BETTER DECISIONS?

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Introduction

This presentation will introduce you to the advantages of using discrete event simulation that, when used correctly, can help you understand and manage complex manufacturing systems such as those found in the forest products industry. Simulation is a powerful analytical tool for designing or experimenting with complex systems. It has been defined as the process of designing a computer model of a real system (existing or proposed) and conducting experiments with this model to either understand the behavior of the system or to evaluate various strategies for the operation of the system (Pegden et al. 1995). It is an experimental and applied methodology to describe the behavior of systems, construct theories or hypotheses to account for the observed behavior, and use the theories to predict future behavior produced by changes in the system or in its method of operation (Shannon, 1975). Simulation is an important tool when the risk involved with modeling is low compared to trial and error with the real system.

Collecting initial data to construct the computer model can be very time consuming. Historical mill data may be used to offset collecting as much new data. Historical data might detail the mix of products flowing through the mill, the grade or specification of different products, machine cycle times, and the amount of downtime for individual pieces of equipment. Historical data can greatly shorten the duration of data collection. One note of caution: historical data is valid only if something has not changed either in the operations or the material mix as products flow through the manufacturing process. If you replaced most of the primary breakdown equipment six months ago in the green end of the sawmill, then historical data over six months old is not going to reflect the new, hopefully improved, process flow through the mill. In this case, all historical data over six months old would reflect a system that no longer exists.

Simulation can be used when actual experimentation with the real system is 1) infeasible, 2) disruptive, and/or 3) too expensive. Use simulation when comparing alternative proposed system designs to see which best meets the specified requirements or when comparing alternative operating policies for a single system to see which best meets the specified requirements.

Deterministic and Stochastic Simulations

A deterministic simulation model assumes no variability in model parameters. Therefore, a deterministic simulation model contains no random variables. An example might be a grading simulator that can be used to determine the economic impact of producing proprietary grades (Reeb, 1991). If a deterministic model is run with the same input values, it will always calculate the same output values.

However, most manufacturing processes exhibit random or unpredictable variables in their environment or components such that 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 (chance) are two factors characterizing all complex manufacturing systems - common for operation times, machine cycles, reject rates, arrival times, downtimes, employee activities, etc. These characteristics make complex systems difficult to study, analyze, and predict. A stochastic simulation model contains random variables to describe the processes in the system being studied. This is an important point to remember. Output data of a stochastic simulation are themselves random, and therefore only estimates of the true characteristics of the model. For a deterministic model, the result of a single simulation run is an exact measure of the performance of the model, but for a stochastic simulation experiment, 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. Statistics are used to provide an estimate of accuracy for the simulation experiment's output.

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. Discrete event simulations are used to analyze overall manufacturing environments, specific issues, and individual measures of performance depending on the proposed problem. Manufacturing environments that can be studied include adding new equipment, upgrading existing machines, changing factory layout, or building a new factory area. Each of the previous items will lead to changes in certain measures of performance for the system. Examples of measures of performance are work-in-process (WIP), part lead times, part throughput, and machine and labor utilization. One of the greatest benefits of using simulation is that a properly designed simulation will give evidence that the chosen plan will perform as required. This lessens the risk when implementing complex and potentially expensive changes (Law 1986).

For manufacturing environments it is important for managers to obtain a system-wide view of the effect of local changes to the system. If a change is made at a particular location, its impact to the process at this location may be fairly predictable, but 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 occurs at a machine center. The product backs up, and sits, at this location. The boss decides to add another machine to eliminate the bottleneck. An additional machine, or an improvement in throughput of the original machine, 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 installation of the new machine. So, another machine is added downstream and this causes other unforseen effects in the process, and so on. Another example: new technology increases the production in the green end of the sawmill by 17%. Can the kilns keep up with this increase? Can the planer keep up with this increase? Will the number of forklifts or kiln cars need to be increased? All of this can be modeled on the computer before the company invests in the new sawmill technology. A simulation experiment might reveal that a new kiln will be necessary and the planer will need to operate another shift to keep up with the expected increase in production. Simulation allows the user to play what-if scenarios, and offers a method of looking at all the changes and their effect on the system without actually disrupting the current system or spending a lot of money.

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