SYSTEM SIMULATION MODELING: A CASE STUDY ILLUSTRATION OF THE MODEL DEVELOPMENT LIFE CYCLE[1]

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ABSTRACT

Systems simulation modeling techniques offer a method of representing the individual elements of a manufacturing system and their interactions. By developing and experimenting with simulation models, one can obtain a better understanding of the overall physical system. Forest products industries are beginning to understand the importance of simulation modeling to help improve the dynamic performance of their processing and manufacturing systems. However, much knowledge and expertise are needed to accurately represent an actual forest products processing system as a simulation model. The purpose of this paper is to describe some effective process simulation model development strategies. This description points to the depth and breadth of knowledge that are needed to create usable and valid simulation models. To assist in illustrating the simulation modeling life cycle, actual case studies in modeling furniture rough mills are used.

Keywords: System simulation, animation, modeling life cycle, integrated decision-support, discrete-event, furniture rough mill.

INTRODUCTION

Analysts predict that the use of computer simulation will rapidly increase during this decade. By the year 2000, it is expected that 40 percent of U.S. manufacturing engineers will be utilizing simulation as a decision support tool. This trend compares to an estimated usage rate of 17 percent in 1988 (Bergstrom 1988). In 1990, the U.S. Department of Defense designated simulation modeling to be one of the 20 most important industrial technologies (U.S. DOD 1990). Evaluation of processing alternatives using simulation will soon be performed on a continual basis by production controllers and engineers just as managerial accountants have adopted the use of spreadsheets to enable them to examine a multitude of "what if" scenarios (Laughery 1990).

Systems simulation modeling provides a means of experimenting with a system that cannot be physically manipulated. Systems modeling joins individual elements of a pro-

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cess together so that the effect of a change in one of these elements on the other elements in the system and on the total system performance can be assessed. With simulation modeling, new production methods can be analyzed for their effect on important output variables, alternative systems can be compared, bottlenecks can be isolated, alternatives for removing bottlenecks can be studied, and sensitivity analyses can be performed.

Forest products industry members are beginning to understand the potential utility of process simulation modeling. Those members who plan to venture into simulation modeling, however, must clearly understand the types of knowledge and decisions that are required during model development. Often, a model's general use is limited owing to the assumptions and data specifications upon which it is based. Several simulation studies have been reported, but they have focused largely on the results of simulation-based experimentation (Anderson 1983; Delamare and Ciccotelli 1992; Meimban et al. 1992; Wiedenbeck 1992). These studies have not addressed the data and expertise requirements of model creation.

The scale of most process simulation modeling projects is quite large. Furthermore, the validity and applicability of a simulation model depend on a complex series of decisions made during the creation phase of the modeling life cycle (Townsend et al. 1988). Our purpose in writing this paper is to demonstrate some effective process simulation model development strategies. We present two case studies of the modeling process to illustrate the simulation modeling life cycle.

SYSTEMS SIMULATION MODELING LIFE CYCLE

The life cycle (Fig. 1) of a comprehensive simulation study consists of multiple study phases and phase transition activities (Nance and Balci 1986; Nance 1981). In the model depicted in Fig. 1, study phases are contained within ovals, and transition activities that drive a study from one phase to the next are indicated by dashed lines. Model credibility assessment occurs upon completion of each developmental activity. Credibility problems frequently force the modeling process to divert back to a preceding study phase. Thus, the development of a comprehensive simulation model may consist of several iterations of the life cycle.

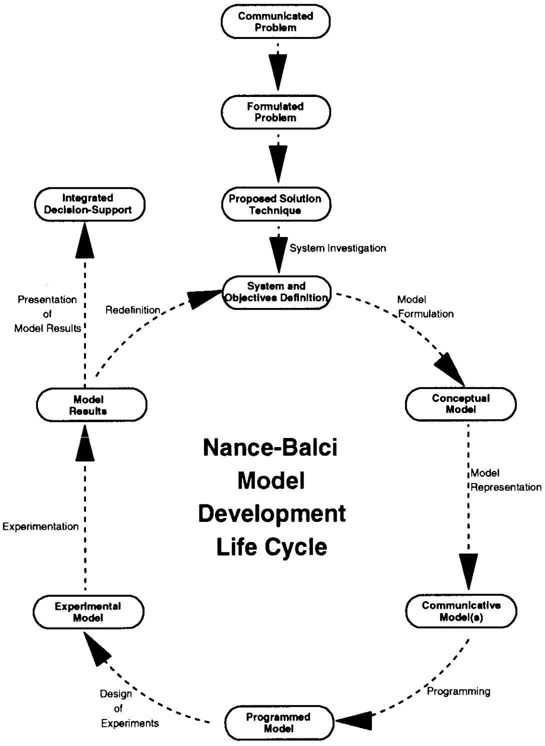

FIG. 1. Nance-Balci Model Development Life Cycle (Nance and Balci 1986). Study phases are contained within ovals and transition activities that drive a study from one phase to the next are indicated by dashed lines.

Prior phases in the simulation modeling Life cycle

There are three phases of the Nance-Balci life cycle model that precede simulation model development (Fig. 1; Nance and Balci 1986). These are the communicated problem phase, the formulated problem phase, and the proposed solution technique phase. A communicated problem, which may have existed for a considerable length of time, leads to research activity to find a solution. While many people may agree that the problem exists, each may define it differently. Work on the problem may be triggered by such factors as: (1) a changing environment that attaches more urgency to the problem, (2) a group decision-maker who recognizes the problem and deems finding its solution important, (3) a researcher who gains understanding of, and interest in, the problem and decides that he/she has the ability to solve it.

Once the importance of a communicated problem has been recognized, the problem must be transformed into a formulated problem. Then, a proposed solution technique must be identified. Problem formulation involves finding a clear definition of the problem and an explicit statement of the problem-solving objectives. These objectives will help identify the best solution technique. Balci (1986) warns against formulating a communicated problem with a given solution technique in mind. If a solution technique is chosen before the problem is adequately defined, unnecessarily expensive solutions that address the wrong problem may result.

Simulation modeling life cycle phases

System investigation, which includes analyses of plant layout, material flows, and activity relationships, is performed during the system definition phase (Fig. 1). These investigations help define the processes and flows that must be included in the model to obtain a sufficiently accurate representation for meeting the stated objectives. During the system definition phase, preliminary data acquisition is frequently conducted. Key system parameters and input and output variables that should be included in the model are identified (Shannon 1975; Balci 1986; Pegden et al. 1990).

The conceptual model is the model that is formulated in the modeler's head. It may be documented, in part, by written observations, flow charts, and abbreviated segments of programming code. It evolves during system observation and investigation and becomes focused when the modeler endeavors to characterize processing and flow relationships. Data collection and analysis activities are a subset of the model formulation process (Shannon 1975; Balci 1986).

The conceptual model is transformed into a communicative model by representing the model orally or visually so that others can understand it. The modeler usually accomplishes this by embellishing personal documentation using charts and diagrams. The communicative model becomes the programmed model when it is encoded using an appropriate simulation modeling tool. Input variable parameters are determined during model programming. During the programming phase, additional system information and data needs are likely to be identified. Model verification, the process of determining that the model executes as expected by the modeler, is performed over and over again during model programming. Animations of simulation models are very useful when trying to pinpoint programming problems; thus they serve a powerful debugging and verification function. Many simulation software packages include computer animation capabilities.

The experimental model includes instructions on simulation run length, the point at which statistics collection begins, and the number of replications of the model. To determine the optimum experimental design, preliminary model runs are conducted (Pegden et al. 1990). Model results are obtained on key output variables. When alternative system configurations are being compared, results are obtained from alternative versions of the model. Statistical comparisons are possible if multiple values for an output variable are recorded for each version of the model. Ideally, a single mean value for each output variable is recorded from each simulation run. Multiple values are obtained by doing model replications, each starting with a different random number seed. This approach assures that the assumptions of independence and normality that exist for most parametric statistical procedures are not violated (based on the Central Limit Theorem).

Model validation, the process of ascertaining whether the model adequately represents reality, is usually based on an assessment of the model results. There are several model validation methods available. The choice of methods depends on whether the system is completely, partially, or not at all observable (Balci 1986). Among the most important are six listed by Balci (1988): "face" validation, field tests, graphical comparisons, predictive validation, the Turing Test method, and statistical comparisons.

The "face" validation method involves discussing the model's output and showing the model's animation to people who are very familiar with the system being modeled (Pegden et al. 1990). These experts are asked to assess the model's apparent validity. In field testing, models are actually placed in an operational setting and real-time data inputs are entered into the model. The model's output is compared with the actual output of the system (Shannon 1975; Balci 1986). For graphical validation, graphs of key simulation model output variables over time are compared with graphs of the actual values of those variables for a similar time frame. Predictive validation involves entering historical system data into the simulation model and comparing the results with the output results generated by the real system. In the Turing Test validation method, a group of experts are shown both simulation model results and actual production results. They are asked if they can make any distinction between the two sets of output. If they cannot, the model's validity is further substantiated. Statistical techniques can be used when the system being modeled exists as a real system and output data from that system can be readily collected (the system is completely observable).

Integrated decision support, in which simulation modeling results are used to facilitate the decision-making process, is possible only if the user group understands the simulation model results and finds them believable. Thus, it is essential that the validity of the model can be demonstrated. The modeler should present graphical representations of the results and concisely worded conclusions that address the study objectives. Model animation can greatly enhance the presentation of results.

FURNITURE ROUGH MILL CASE STUDIES

Prior phases in the simulation modeling life cycle

A flow chart showing the specific modeling steps taken during our study of the effect of lumber length on rough mill productivity is given in Fig. 2. The three phases of this study that preceded simulation model development —problem identification (the communicated problem), problem formulation, and the choice of a solution technique — required a yearlong investigation. The majority of this time and effort was spent in problem formulation.

The problem that triggered this study was that no significant market for short (shorter than 8 feet long) hardwood lumber existed. The communicated problem has been stated in many ways for many years: "Sawmills won't produce short lumber"; "The hardwood lumber grading rules discriminate against short lumber"; and "Short lumber can't be run in our system" were typical statements. After a lengthy orientation period, we came to realize the problem that needed to be investigated was the legitimacy of the notion held by furniture and cabinet manufacturers (the major market for the middle and upper grades of hardwood lumber) that short lumber could not be profitably used in their operations.

Discrete-event systems simulation modeling was chosen as the solution technique for this problem. Several reasons led to this choice: (1) opportunities to observe processing of short lumber in furniture/cabinet rough mills are extremely limited, (2) rough mill experiments designed to collect throughput and part value data would be very disruptive to the rough mill operation, and (3) short lumber handling problems that might exist in an actual rough mill would complicate a mill study experiment and bias the results. In a simulation model, the assumption that short lumber handling problems could be corrected can be implemented

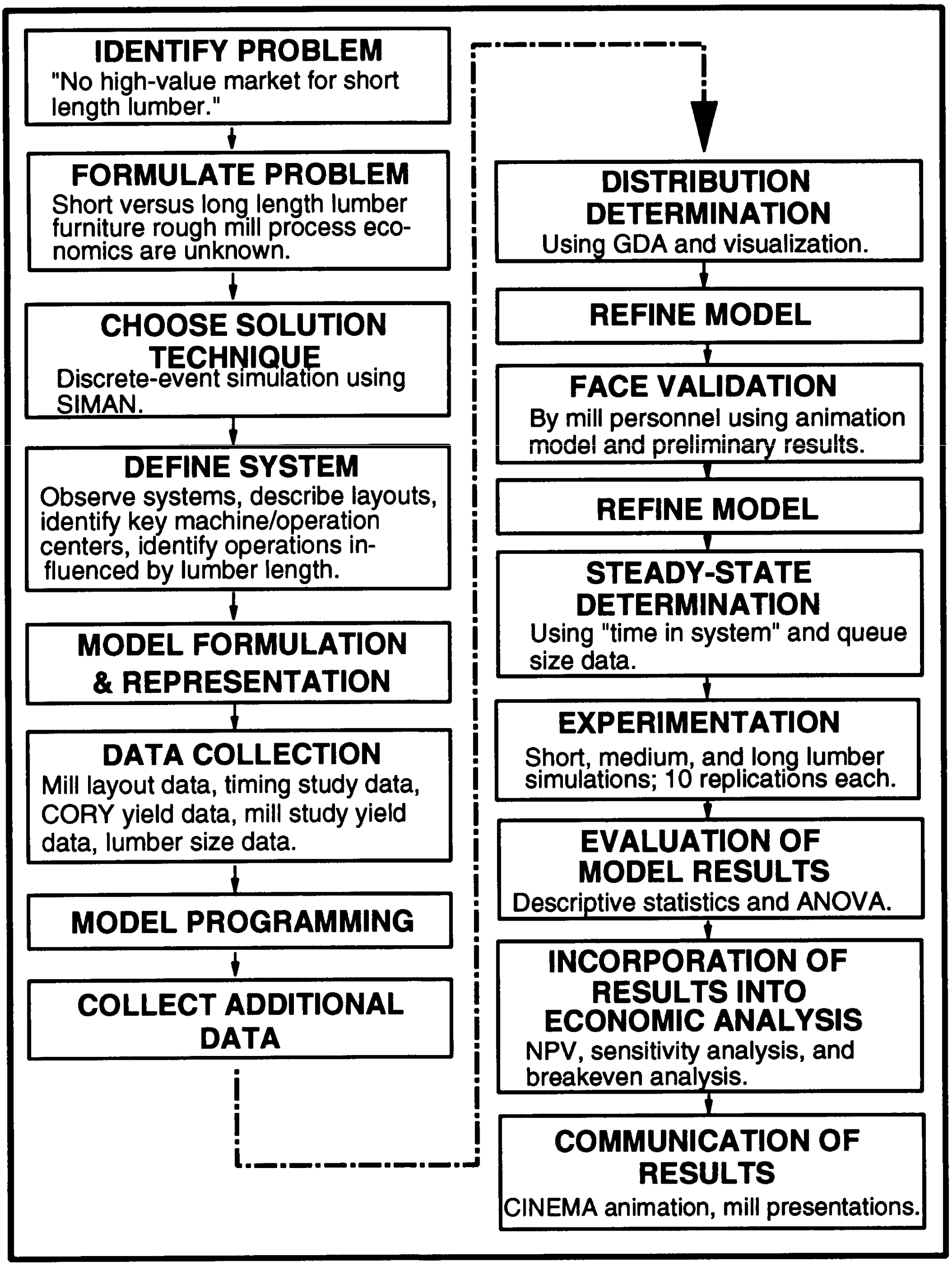
IDENTIFY PROBLEM
"No high-value market for short length lumber."
FORMULATE PROBLEM
Short versus long length lumber furniture rough mill process economics are unknown.
CHOOSE SOLUTION TECHNIQUE
Discrete-event simulation using SIMAN.
DEFINE SYSTEM
Observe systems, describe layouts, identify key machine/operation centers, identify operations influenced by lumber length.
MODEL FORMULATION & REPRESENTATION
DATA COLLECTION
Mill layout data, timing study data, CORY yield data, mill study yield data, lumber size data.
MODEL PROGRAMMING
COLLECT ADDITIONAL DATA
DISTRIBUTION DETERMINATION
Using GDA and visualization.
REFINE MODEL
FACE VALIDATION
By mill personnel using animation model and preliminary results.
REFINE MODEL
STEADY-STATE DETERMINATION
Using "time in system" and queue size data.
EXPERIMENTATION
Short, medium, and long lumber simulations; 10 replications each.
EVALUATION OF MODEL RESULTS
Descriptive statistics and ANOVA.
INCORPORATION OF RESULTS INTO ECONOMIC ANALYSIS
NPV, sensitivity analysis, and breakeven analysis.
COMMUNICATION OF RESULTS
CINEMA animation, mill presentations.

FIG. 2. Flow chart of simulation modeling process.

and unbiased estimates of the potential production rates for short lumber can be obtained. By combining the model's output (value of cuttings produced per hour) with multiple economic assumptions on direct and indirect production costs and capital investment rates, we were able to appraise the profitability of processing short length lumber.

A PC-based simulation software programming language, SIMAN (Systems Modeling Corporation[2]), was chosen as the development tool. A screen show, or animation of the simulation, was programmed using a companion software routine called CINEMA. Animation provides a means of verifying and validating the model. The animation feature was also valued as a means of demonstrating the model to industry personnel in order to increase the credibility of the results.

System definition

The first step in the system definition phase was to identify crosscut-first and rip-first rough mill cooperators. The cooperating mills contributed both access and information on a continual basis during the yearlong modeling process. Other elements of the system definition phase included: drawing the mill layouts (Fig. 3), measuring conveyor distances and speeds, talking with production management personnel about lumber length-based issues, and observing the systems in operation.

A good working understanding of the system to be modeled should be acquired by the programmer during the earliest stages of model development. While performing "system definition" activities, many model formulation ideas can be considered. Since complex material flows can easily be miscommunicated, it is important for the person who will be programming the model to be involved in system definition. Frequently, a person with considerable knowledge of the system can provide copious information on material flows and equipment specifications to the modeler/programmer. This might tempt the model's programmer to limit involvement in the system definition and model conceptualization phases. In the long run, however, this can lead to delays and backtracking when credibility tests expose model validity problems.

Data collection

Data collection activities are a part of the model formulation process. For many simulation problems, data, either manual or computerized, will be available from the mill/company (Townsend et al. 1988). However, all input data needed for this simulation model had to be collected at each mill. None was available from the cooperators as lumber length-based productivity rates had not previously been studied.

Initially, exploratory time studies on various operations were conducted. It soon became clear which operations were most affected by lumber length and piece counts. These operations became the focus of subsequent time studies. An attempt was made to capture between-operator variability by gathering data on multiple operators per operation.

Additional data were collected during mill studies conducted at each rough mill. The cutting bills used in the mill studies were selected by the rough mill supervisors. An attempt was made to choose a cutting bill that would match up well with the short length lumber input. The piece rates and cutting length distributions associated with these cutting bills were key input variables for the simulation models. Additional time data were also collected during the mill studies. These data, gathered at each of the primary rough mill cutup operations, consisted of single operator timings, by lumber length and grade.

Less specific simulation models, like this one, are usually self-driven (Kobayashi 1978). Variable values in self-driven models are based on probabilistic distributions specified by the modeler. Occasionally, a highly specific sim-

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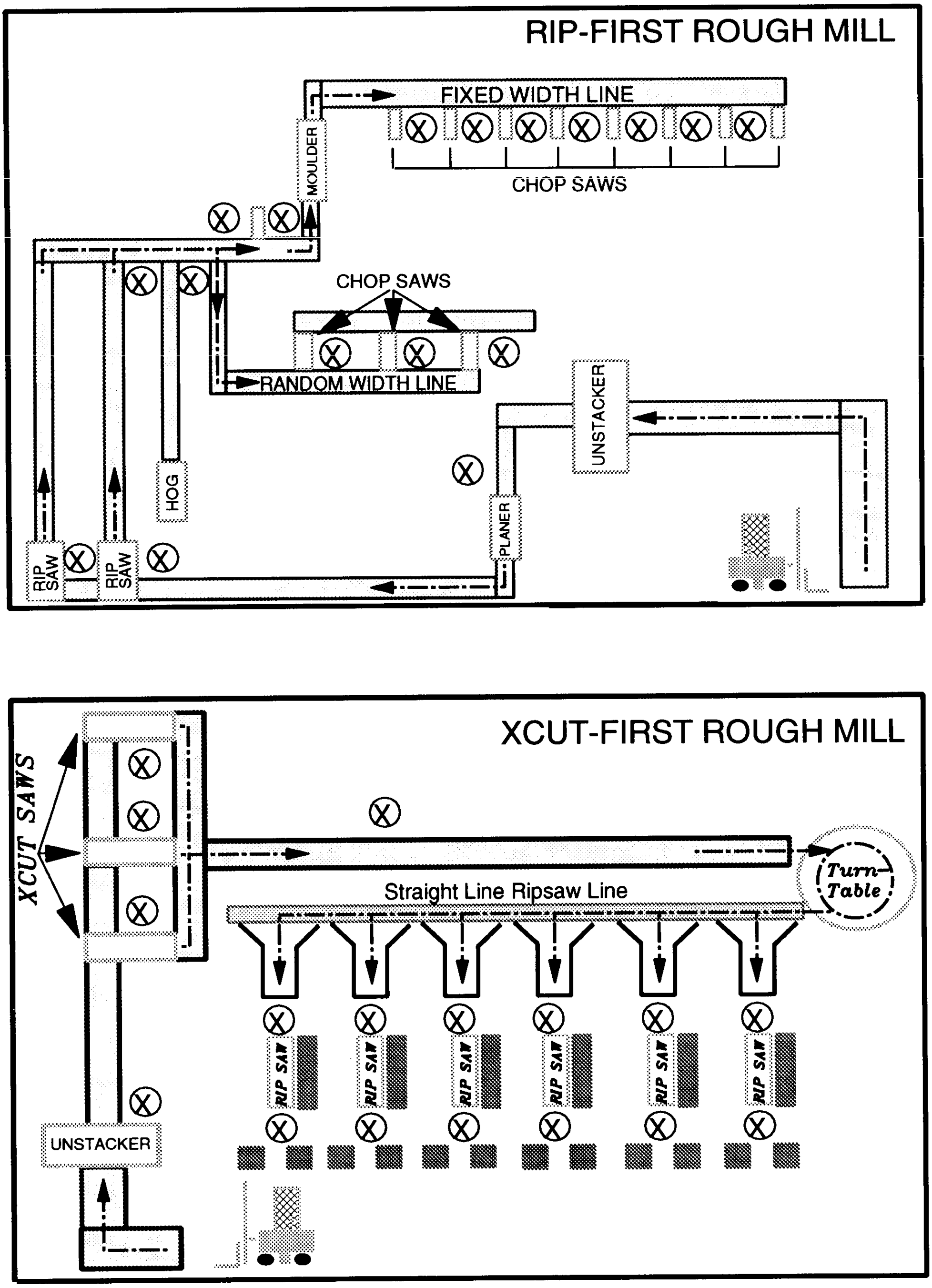

FIG. 3. Rip-first and crosscut-first rough mill layouts used is simulation models.

ulation model will be trace-driven (Kobayashi 1978). Trace-driven models are driven by a series of numeric inputs of actual data from the real system. For instance, rather than sampling from a distribution, actual board length and width data could have been entered into the simulation model. A very large body of data needs to be available to run a trace-driven simulation. This type of data is becoming more available as scanners and automated data recorders are being utilized in many production environments.

Model programming

The translation of the rough mill system information into the simulation programming language was attempted first with the rip-first model. During the programming process, it was discovered that some time elements had been inadequately defined. For example, in timing the ripsaw throughput rates, several operational elements had been aggregated together. Some of these elements were highly dependent on lumber length (e.g., the time for board to clear the ripsaw), some were somewhat length-dependent (e.g., the time required for the operator to flip and straighten boards entering the ripsaw scanning station) and some had no length-dependency (e.g., the time required to reposition the ripsaw's fence before each board is processed). These elements had to be separated and retimed to adequately capture lumber length-based differences in rough mill processing rates.

During the initial stages of the programming process, certain complex material flow relationships were simplified. These flow relationships were studied on subsequent visits to the cooperating mills to acquire the necessary level of modeling accuracy.

Different versions of both the crosscut-first mill model and the rip-first mill model were assembled for each of three lumber length groupings: short (4 through 7 feet nominal measure), medium (8 through 13 feet), and long (14 through 16 feet). The main difference between these versions was in the distribution parameters for the various service rates and board attributes (i.e., lumber length, width, and grade; and cutting sizes). However, differences between the distributions sometimes created material flow problems in one model that were nonexistent in the other models. In these cases, additional programming was required to establish a realistic form of flow control.

The rip-first rough mill simulation model described in this paper contained approximately 1,450 lines of code. This program, comprehensive as it was, did not require any external subroutines. It utilized 98 percent of the PC's conventional memory during compilation and execution. It took approximately two months to define the rip-first system and collect the needed data and five months to program this model. The crosscut-first rough mill computer program contained approximately 850 lines of code. The developmental time for this model was approximately half as long as for the rip-first model. This difference in development time reflects: (1) the learning that took place on the simulation modeling language, (2) the learning that took place in data collection, (3) the difference in the size and complexity of the two rough mill systems that were modeled.

Distribution determination

After the first translation of each model was completed, the task of determining the appropriate distributions to associate with the different machine throughput rates and material parameters was undertaken. The first decision that had to be made about the input data was which data to use for those operations that were timed in both the short lumber mill studies and the large-scale time studies.

Timings that were taken during the mill studies (crosscut-saw rates during the crosscut-first mill study, ripsaw rates and fixed width chop saw rates during the rip-first mill study) were limited in several regards: (a) only one operator was timed, (b) a limited number of observations per operation were recorded, and (c) the grades were segregated rather than mixed as is the case with the normal lumber input into the rough mills modeled. However, these mill study-based timings did provide some limited data on short length lumber service rates that were not otherwise available. These short lumber service rate data were used to check the short lumber service rate values that were extrapolated from the large-scale time studies. For each of the operations timed in the mill study, the mean value for the timings fell within the 950/0 confidence interval of the mean value obtained through extrapolation.

Time study and board data collected at the cooperating mills were plotted in histogram form, and candidate distributions were visually identified. Analysis of variance tests were conducted in those cases where the data distributions indicated a correlation with lumber length. The data were grouped into three length categories for these analyses. The data were then analyzed with the Graphic Distribution Analysis program (GDA; Worley et al. 1990). The GDA program performs a statistical comparison of a parameter's actual data distribution and the distribution that would be expected if the data conformed perfectly to the given probability function (e.g., Weibull, normal). The GDA analyses were sometimes difficult to apply because the data for one of the length groups demonstrated one type of distribution while the data for another length group indicated that a different candidate distribution was more appropriate. In these cases, and in cases where the amount of data collected was thought to be insufficient, a triangular distribution was also considered. The minimum and maximum points for the triangular distribution were chosen from the pooled mill study and time study data. The "most likely" parameter estimate was based on histograms of the time study data.

The distribution of cutting lengths obtainable from red oak lumber was estimated using the data obtained from running the two-stage version of the lumber cut-up program CORY (Brunner et al. 1989) and red oak board data files that were assembled at the U.S. Forest Service's Forestry Sciences Laboratory in Princeton, West Virginia (Gatchell et al. 1992). For both the crosscut and rip-first models, both the mill study-based cutting length distributions and feasible alternative cutting length distributions were incorporated into the simulation models. The alternate distributions were included to offer an estimate of the variability that might be expected given a slightly different cutting bill or a slightly different cutting length demand schedule.

For several of the less precise rip-first distribution estimates, the simulation model was run successively with first one, and then another of the distributions under consideration. This was done in order to determine if the distribution choice impacted the experimental results. If so, additional data would need to be collected. Table 1 shows the distributions that were investigated in this manner. Ten replications of each of these distribution-check runs were executed. T-tests were conducted on some of the more critical simulation output results compiled from these runs. For a couple of the iterations, some small differences were detected in one or two of the machine utilizations measured, but none of the output volume and yield variables varied between runs. Triangular distributions were selected for the final experimentation runs for each of the parameters listed in Table 1. The triangular distribution is a good choice when the data do not strongly indicate that another distribution is appropriate. Estimates of the parameters of a triangular distribution — the minimum, maximum, and most likely observation levels — are usually available.

Model verification and validation

Model animations were built in parallel with the simulation models and proved to be very valuable in model debugging and verification activities. The learning curve for a particular simulation programming language quickly approaches its maximum level once the programmer learns the tricks involved in debugging a model.

The models were shown to the cooperators using the animation feature, for purposes of structural or "face" validation. Results from the simulation runs were discussed and ques-

TABLE 1. *Rip-first rough mill simulation candidate distribution comparison based on part volume production per hour.*

Parameter–lumber length group	Distributions compared[a] (seconds)	Output vol per hour (mean) bf	Significance of difference
FIXED CHOP RATE	NORM (16.99, 4.62)	2,804	NS[b]
PER CUTTING–Med.	NORM (15.41, 2.97)	2,810	
FIXED CHOP RATE	TRIA (7, 15.5, 29.5)	2,816	NS
PER CUTTING–Med.	NORM (15.41, 2.97)	2,810	
FIXED CHOP RATE	TRIA (7, 15.5, 29.5)	2,816	NS
PER CUTTING–Med.	NORM (16.99, 2.97)	2,804	
RIP SAW LASER	TRIA (6.3, 7.3, 18.9)	2,674	NS
SCAN RATE–Long	WEIB (6.3, 3.2, 1.1)	2,688	
CHOP SAW BUFFER	TRIA (2.5, 2.8, 4.8)	2,674	NS
RELOAD RATE–Long	WEIB (2.2, 1.0, 2.5)	2,694	

[a] Distribution notations used are: TRIA — triangular, NORM — normal, WEIB — three-parameter weibull.

[b] NS stands for “not significant” . . . *t* - tests conducted on the output from 10 replications of each model showed the groups were not significantly different (= 0.05)

tions concerning various flow relationships were posed. For the rip-first mill, several suggestions for improving the model were made and two additional weeks of programming were required. The crosscut-first simulation model was found to be acceptable by mill personnel.

Steady-state determination

Steady-state is the term used in process simulation modeling to indicate the condition in which entities (e.g., lumber, strips, pieces, cuttings) are distributed throughout the system in a pattern indicative of continuous production mode. When modeling an operation in which entities are rarely emptied from the system (referred to as a non-terminating system), it is important to be able to differentiate start-up state from steady-state in the model. The beginning of steady-state was determined for each of the models by collecting data on queue sizes and the length of time that an entity resided in the system. Data collection on these variables began at time zero and proceeded for several thousand simulated seconds until a repetitive timing pattern emerged.

In both the crosscut-first and rip-first models, the long length lumber group produced so many pieces at the first breakdown operation that the second stage cut-up operation's queues backed up steadily until a control mechanism within the models was triggered. In the crosscut-first model the control mechanism was the switching of a rip-saw operator from a low volume cutting length onto the highest volume cutting length to help reduce the material flow imbalance. This control mechanism was activated whenever the high volume ripsaw's buffer accumulated more than 175 pieces. For the rip-first mill, the flow control mechanism used was the shut down of the ripsaws when more than 50 strips were in the moulder queue. Steady-state was reached in both of these models at some point in time after the flow control mechanism was activated.

Figure 4 demonstrates the type of information used to determine steady-state for the crosscut-first rough mill model. Time $T_{7,000}$ (7,000 seconds into the simulation) was chosen as the beginning of the steady-state period for the crosscut-first model through visual inspection of this and similar graphs, and through the application of a startup heuristic (Wilson and Pritsker 1978). The heuristic indicates that “startup,” or the start of steady-state, should be set such that the plotted value line intersects the mean value line (the mean value for the variable under consideration during a simulation run that begins at the estimated startup time; e.g., time $T_{7,000}$) a specified number of times (in this case three times). This graph is from the long length lumber version of the crosscut-first model. The same evaluation pro-

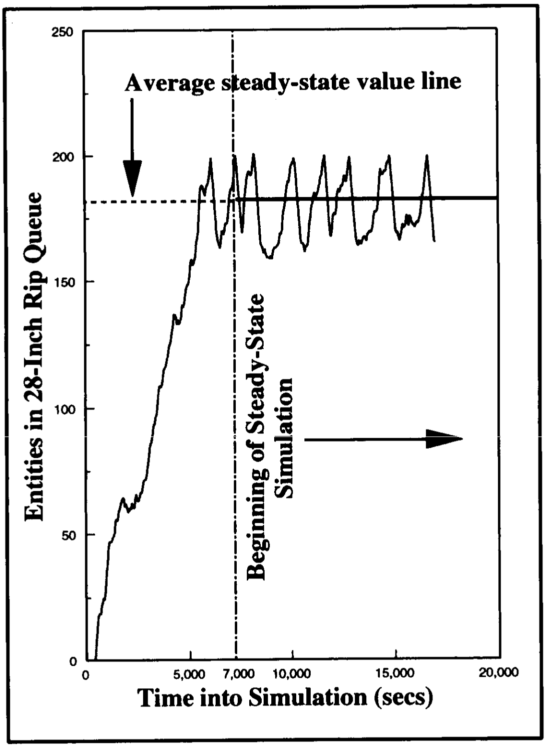

FIG. 4. Crosscut-first model steady-state determination graph. Time $T_{7,000}$ was chosen as the beginning of steady-state based on this and other graphs.

cess was used to determine the end-point of the initial transient phase for the short and medium length lumber versions of the model.

All of the versions of the rip-first model reached steady-state more rapidly than did the crosscut-first models. Since the bottlenecks in this system were the unstacker and planer (for the short lumber) and the moulder (medium and long lumber), both of which receive a high volume of material soon after start-up, the flow control system was activated relatively early in the simulation.

Experimental design

Before experimentation could begin, decisions had to be made as to how to collect the necessary data from the models. The disadvantage of having an experimental design consisting of one long simulation run, rather than several shorter runs, is that data correlation may pose a problem when analyzing output from a single simulation. When multiple simulation runs are used, statistics can be conducted on the mean values of the output variables. The Central Limit Theorem indicates that these values will be independent and normally distributed. However, the use of replicates can be time-consuming if a long, initial transient stage is discarded for each replication. Memory limitations inherent in the current version of SIMAN restricted the use of the SIMAN Output Processor's filtering tool. The filtering tool can provide an alternative method of estimating the variance of the output values.

Using standard statistical procedures, the required number of model replications can be estimated based on the variability of key output variables measured in a smaller scale prestudy. Ten replications were run for each of the versions of the two models. Statistics were collected on the rip-first model for 1,800 simulated seconds (½ hour) starting at the predetermined steady-state beginning point. Test runs of longer duration were conducted to ascertain that 1,800 seconds was a sufficiently long simulation period. The output from the longer runs was not significantly different from the output of the 1,800-second-long simulation runs. The rip-first system is a nonterminating system that requires steady-state treatment. When cutting bill changes are made, they frequently occur in a piecemeal fashion and they seldom affect any of the operations preceding the chop saws. The rip-first system is rarely emptied to the point that operators begin a shift or a cutting bill in the idle state with empty buffers.

For the crosscut-first simulation model, both steady-state and start-up state replication sets were executed for each version. The start-up state simulation runs were considered more valid for the crosscut-first mill than were the steady-state runs. At the crosscut-first mill represented by this model, several wholesale cutting bill changes are made daily. During the new cutting bill set-up period, the crosscut saws are shut down for several minutes while the operators change the jig positions on the front gauges. In almost all cases, the ripsaw operators manage to clear their infeed buffers during this set-up period. This, in effect, creates a terminating system with a fixed starting condition (rip-saws and sorting system idle and empty). The average length of time spent working on a given cutting bill at this mill is approximately 1½ hours. Thus, statistics were collected on the crosscut-first simulation runs for 5,400 seconds.

Experimental results

For the crosscut-first mill model, the volume and value of parts produced from short lumber compared favorably with the volume and value of parts produced from the medium (8–13 feet) and long (14–16 feet) lumber. A "pessimistic case" short lumber scenario was also simulated in which the distribution of cutting lengths was varied. The short lumber volume and value yields for this model version were somewhat lower than the medium and long yields.

For the rip-first mill model, the volume and value of parts produced from short lumber was equal to approximately 60 percent of the production from the medium and long length lumber. The unstacker and planer were unable to provide sufficient material to the ripsaws, which in turn were unable to process the short lumber fast enough to keep the chop saws busy.

A more complete description of the short lumber processing analysis, results, and interpretation can be found in Wiedenbeck (1992, 1993).

SUMMARY AND CONCLUSIONS

This paper describes a methodology for process simulation modeling and illustrates the depth and breadth of the knowledge needed to create a usable and valid model. Appropriately representing a manufacturing system's complex material flows and process interactions is the key to the successful development of a usable simulation model. Also, properly designed experimentation with the models is crucial if valid results are to be obtained. The extent of the knowledge and understanding involved in the simulation model development life cycle was demonstrated using case studies of furniture rough mill systems.

The simulation modeling project described in this case study was quite large. However, numerous simulation modeling projects require the integration of many more operations. This imposes additional modeling complexity and increases the length-to-completion of the modeling life cycle. Also, if a large number of people feel they have a stake in a modeling project, each of the life cycle phases will expand. This may improve the validity of the resultant model. However, validity must be considered within the proper context. It is not valid to spend an inordinate amount of time modeling details when relative system performance can be determined with a less specific model.

The investment in time and money that must be committed by a company at the outset of a modeling project may seem steep. Thus, some companies opt to have a consultant do their modeling for them. However, the company that does its own modeling ends up with: (1) a model that can be readily expanded, (2) modeling expertise that can be readily applied to future problems, and (3) a new and more comprehensive understanding of their system's material flow relationships, interactions, and problems.

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