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PITFALLS IN THE SIMULATION OF MANUFACTURING SYSTEMS

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ABSTRACT

There has been a significant increase in the use of simulation to design and analyze manufacturing systems during the last few years. However, in many of these simulation studies the major emphasis has been on programming, with relatively little consideration being given to model validity and statistical issues. In this paper we discuss ten potential simulation pitfalls in the areas of model development, simulation software, modeling system randomness, and design and analysis of simulation experiments.

1. INTRODUCTION

There has been a dramatic increase in the use of simulation in manufacturing during the past few years. This has been caused by the increased complexity of automated systems, reduced computing costs, improvements in simulation languages, and the availability of graphical animation. However, there is an unfortunate impression that simulation is just a complicated exercise in computer programming. Consequently, many simulation "studies" have been composed of heuristic model building, coding, and a single run of the program to produce the "answers." This attitude, which neglects the important issues of how to develop a valid model and how to draw correct inferences about the system of interest, has led to simulation results not being used in the decision-making process and to the development of manufacturing systems which are either inadequate or contain unnecessary resources.

In this paper we discuss ten pitfalls awaiting the unwary simulation analyst; these pitfalls are broken into four sections corresponding to different aspects of a typical simulation study. After stating each pitfall, we will describe the potential implications of the pitfall and (if appropriate) give references to materials on how this pitfall can be avoided. In some cases we will also present actual simulation results to illustrate definitively the consequences of a particular pitfall.

2. SIMULATION MODELING

In this section we discuss pitfalls which correspond to the problem formulation and model development (prior to coding) phases of a simulation study.

Pitfall Number 1: Failure to Have a Well-Defined Set of Objectives

Since simulation models of manufacturing systems are generally not valid for all questions of interest, it is important to have a clear statement of the study's objectives. This allows the analyst to decide what aspects of the real system should and should not be included in the model; it is not necessary to have a one-to-one correspondence between every aspect of the system and every aspect of the model. The measures of performance that will be used for comparing alternative system designs should also be clearly delineated. A simulation model may be accurate enough to predict the throughput of a proposed manufacturing system, but may not be adequate to determine the sizes of the storage areas required for work in process.

Pitfall Number 2: Treating a Simulation Study as a Programming Exercise

There has been a tendency in many organizations to view simulation as primarily a programming exercise. Consequently, these organizations have placed a large emphasis on selecting an appropriate simulation language, training their personnel in that language, and then coding the simulation model in the selected language. Although these activities are certainly important aspects of a successful simulation study, we believe that members of the modeling team need additional knowledge and skills. In particular, at least one modeler or analyst must intimately understand the manufacturing system to be modeled and also have a strong background in probability and statistics. (A knowledge of operations research techniques, particularly the behavior of queueing systems, is also useful.) Probability and statistics are needed throughout the entire simulation study, from model development to the analysis of the simulation output data (see Law 1986 and Law and Kelton 1982).

Pitfall Number 3: Failure to Communicate with Management on a Regular Basis

It is extremely important for a simulation analyst to interact with the appropriate manager on a regular basis. This will help ensure that the right problem is being solved, that the knowledge of the manager is being incorporated into the model (which increases model validity), and, perhaps most importantly, that the manager understands and agrees with the model's assumptions. Managers or decision makers are much more likely to accept as valid and to use models in whose development they were actively involved.

3. SIMULATION SOFTWARE

Improvements in simulation languages have reduced the time required to model a manufacturing system. This has resulted in greater use of simulation in manufacturing, since many manufacturing projects operate on a very short time frame. Furthermore, the availability within the last few years of graphical animation has resulted in greater understanding and use of simulation by engineering managers. Although these developments have been very beneficial to the manufacturing simulation community, the reader should be aware of certain associated pitfalls.

Pitfall Number 4: Software which Makes Simulation Accessible by "Anyone"

There are several simulation products now available which allow a person to simulate a particular system within a specified class of manufacturing systems in a very short period of time. These simulators are usually menu or graphics driven and require little or no programming. They are particularly attractive when a "coarse" model of a manufacturing system needs to be developed quickly. They are also of great interest to people with little or no background in the fundamentals of simulation who want to "simulate" their system with little effort (e.g., programming). We believe that this is potentially dangerous since the successful completion of a simulation study requires knowledge of such issues as validation, input modeling, and output data analysis.

Pitfall Number 5: Misuse of Animation

There apparently have been situations where a manager made a decision on the suitability of a particular manufacturing system design on the basis of an animation run for a very short amount of time. (In one case, a manager insisted on making a decision based on an animation driven by an undebugged simulation.)

There are several animation packages which operate as the simulation actually executes, rather than being post-processers. Several of these allow an analyst to stop a simulation during execution, change the parameters of the simulation, and then continue execution for this "new" system design. This is potentially dangerous since the ending conditions for the original (perhaps ill-defined) simulation may not be "typical" initial conditions for the new simulation. Also, the simulation/animation package may not clear the statistical counters between the two simulation runs as desired.

4. MODELING THE RANDOMNESS IN A MANUFACTURING SYSTEM

Most manufacturing systems contain one or more (input) sources of randomness (random variables). Interarrival times of jobs at a machine, processing times of jobs at a machine, machine running times before breakdown, machine repair times, and the outcomes of inspecting jobs (e.g., good, rework, or scrap) are possible examples of random variables in a manufacturing system. Furthermore, in order to model the system correctly, each random variable must be represented by an appropriate probability distribution in a simulation model. In this section we discuss pitfalls related to the choice of these distributions.

Pitfall Number 6: Replacing Distributions by Their Means

Sometimes an analyst might use the mean of a distribution rather than the distribution itself to model a source of randomness in a manufacturing system. (This may be done for reasons of convenience or due to lack of data.) To illustrate the potential danger in this practice, consider a system consisting of a single machine as shown in Figure 1. Jobs (or work pieces) arrive at the machine tool for processing. If the machine is idle when a job arrives, processing begins immediately. Otherwise, the job joins the end of a queue. When the machine finishes processing one job, it begins processing the first job in queue (if any).

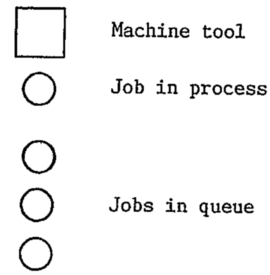

Figure 1: Single Machine Tool System

Suppose for the actual system that the interarrival times of jobs have an exponential distribution [see Law and Kelton (1982, p. 159)] with a mean of 1 minute and that the processing times of jobs have an exponential distribution with a mean of 0.99 minute. Then it can be shown that in the long run there will be an average of approximately 98 jobs in the queue and each job will spend approximately 98 minutes waiting in the queue. On the other hand, suppose that we replace the two distributions by their means. That is, suppose each interarrival time is exactly 1 minute and each processing time is exactly 0.99 minute. Then it is clear that no customer ever waits in the queue in this erroneous model of the actual system.

In general, it is variability rather than means which causes congestion in queueing (e.g., manufacturing) systems.

Pitfall Number 7: Incorrect Choice of Input Probability Distributions

We have seen above that, in general, a probability distribution must be used to represent a source of randomness in a manufacturing system. One might next ask whether the distribution selected will have a significant impact on the estimated measures of performance produced by the simulation. To shed some light on this question, consider the single machine tool system (Figure 1) with exponential interarrival times, but with an unknown processing time distribution. Suppose that a set of actual processing times were available and that we "fit" the best possible exponential, gamma, Weibull, lognormal, and normal distributions to these data. We then made 100 independent simulation runs of the system for each of the five candidate processing time distributions; thus, there were a total of 500 runs. Each simulation was run until 1000 delays in queue were completed. The average results across the 100 runs for each distribution are given in Table 1. Since the Weibull distribution provided the best fit for the historical processing times, its results in Table 1 can be considered the standard for comparison. Note that the average delay for the well-known normal distribution differs from the average delay for the "correct" Weibull distribution by 39 percent. Surprisingly, the use of a lognormal distribution, which has a shape similar to the Weibull distribution, resulted in an even larger error in average delay of 65 percent.

Techniques for deciding what probability distribution best fits a set of observed data are discussed in Law and Kelton (1982, chapter 5) and Law and Vincent (1985).

Table 1: The Effect of Different Processing Time Distributions

Distribution	Average delay	Proportion of delays ≥ 20
exponential	6.71	0.064
gamma	6.54	0.019
Weibull	4.36	0.013
lognormal	7.19	0.078
normal	6.04	0.045

Pitfall Number 8: Incorrect Modeling of Machine Breakdowns

Probably the major source of randomness in most manufacturing systems is that associated with the breakdown and repair of machines. The following example illustrates the danger in not modeling breakdowns correctly.

Suppose that a company is going to buy a new machine tool (see Figure 1) from a vendor who claims that the machine will be down 10% of the time. However, the vendor has no data on how long the machine will operate before breaking down or on how long it will take to repair the machine. Historically, some analysts have accounted for random breakdowns by simply reducing the processing rate by 10%. We will see, however, that this can produce quite inaccurate results.

Suppose that the single machine tool system will actually operate in accordance with the following assumptions when installed by the purchasing company:

a) Jobs arrive with exponential interarrival times with a mean of 1.25 minutes.
b) Processing times for a job at the machine are a constant 1 minute.
c) The machine runs for an exponential amount of time with mean 540 minutes (9 hours) before breaking down.
d) The repair time for the machine has a gamma distribution (shape parameter equal to 2) with mean 60 minutes (1 hour).
e) The machine is, thus, broken 10% of the time.

In column 1 of Table 2 are results from five independent simulation runs of length 160 hours (20 8-hour days) for the above system. In column 2 of the table are results from five simulation runs of length 160 hours for the machine tool system with no breakdowns, but with the processing (cycle) rate reduced from 1 job per minute to 0.9 job per minute. (This has sometimes been the approach of simulation practitioners.) The results in the first three rows of the table are averages across the five runs, while the results in the last row are maximums across the runs.

Note first that the weekly throughput is almost identical for the two simulations. (For a system with no bottlenecks which is simulated for a long amount of time, the throughput for a 40-hour week must be equal to the arrival rate for a 40-hour week, which is 1,920.) On the other hand, note that such measures of performance as mean time in system for a job and maximum number of jobs in queue are vastly different for the two cases. Thus, the deterministic adjustment of the processing rate produces results which differ greatly from the correct results based on actual breakdowns of the machine.

Table 2: Simulation Results for the Single Machine Tool System

Measure of performance	Breakdowns	No breakdowns
Throughput per week	1908.8	1914.8
Mean time in system	35.1	5.6
Average number in queue	7.3	3.6
Maximum number in queue	231	35

5. DESIGN AND ANALYSIS OF SIMULATION EXPERIMENTS

In this section we discuss pitfalls related to the design of simulation experiments (e.g., number of runs and their length) and to the analysis of the resulting simulation output data.

Pitfall Number 9: Making Only One Simulation Run for a Particular System

One of the most common (and potentially dangerous) practices in simulating manufacturing systems is that of making only one run (or replication) of a stochastic simulation. To illustrate this point, consider a simple manufacturing system consisting of a machining center and an inspection station, as shown in Figure 2. Suppose that the system operates according to the following assumptions:

a) Jobs arrive at the machining center with exponential interarrival times with a mean of 1 minute.
b) Processing times at the machining center are uniform on the interval [0.7, 0.8] minutes.
c) After processing, jobs proceed to the inspection station where inspection times are uniform on the interval [0.8, 0.9] minutes.
d) Ninety percent of the inspected parts are good and are sent to shipping; ten percent are bad and must be re-machined.
e) The machining center is subject to randomly occurring breakdowns. In particular, a new (or freshly repaired) machining center will break down after an exponential amount of time with a mean of 6 hours.
f) Repair times are uniformly distributed on the interval [8, 12] minutes.

In Table 3 we give selected results from five independent simulation runs of the manufacturing system (i.e., different random numbers are used for each run), each of length 16 hours. Note that results from different runs can be quite dissimilar. Thus, it is clear that one simulation run does not produce the "true answers" for the simulated system.

If we want to estimate the expected daily throughput, the average throughput across the replications (see the last row of the table) will be a better estimate, in general, than the observed throughput from only one run. Also, the maximum queue size in the

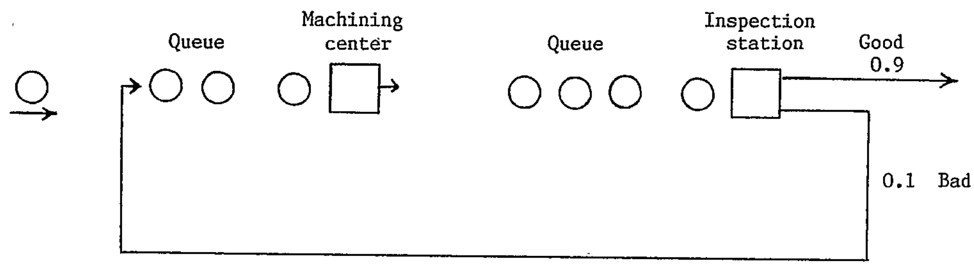

Figure 2: Manufacturing System with Inspection Station

last row of the table may be important in designing a manufacturing system because it is indicative of the amount of storage required for in-process inventory.

Table 3: Simulation Results for Simple Manufacturing System with Breakdowns

Run	Throughput	Average time in system (minutes)	Maximum number in inspector queue
1	972	19.0	33
2	922	7.6	12
3	963	20.6	53
4	930	6.4	9
5	896	7.1	12
Average or Maximum	936.6	12.1	53

Pitfall Number 10: Failure to Warm-Up a Simulation Model

When simulating manufacturing systems, we are often interested in the long-run behavior of the system, i.e., its behavior when operating in a "normal" manner. (In the previous example, we were interested only in the behavior of the system over a 16-hour day.) On the other hand, simulations of manufacturing systems often begin with the system in an empty and idle (or some other unrepresentative) state. This results in the output data (e.g., daily throughputs) from the "beginning" of the simulation not being representative of the desired "normal" behavior of the system. Therefore, simulations are often run for a certain amount of time, the warm-up period, before the output data are actually used to estimate the desired measures of performance.

A graphical approach for determining the length of the warm-up period is given in Kelton (1986).

There are two additional pitfalls related to the design and analysis of simulation experiments. They are analyzing simulation output (e.g., estimating variances) using formulas which assume independence [see Law and Kelton (1982, chapter 4)] and comparing alternative system designs using only one simulation run for each system [see Law and Kelton (1982, chapter 9)].

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