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SECRETS OF SUCCESSFUL SIMULATION STUDIES

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ABSTRACT

In many "simulation studies" the primary focus is on simulation software selection and "programming." We believe, however, that only 30 to 40 percent of the total effort in most successful simulation projects is actually model coding. In this tutorial we discuss ten key steps that should, in fact, compose a sound simulation study.

1 INTRODUCTION

The use of simulation modeling to design new systems and to "fine-tune" the performance of existing systems continues to increase at a rapid pace due to the increased complexity of contemporary systems, reduced computing costs, improvements in simulation software, and the availability of animation. However, there still is the unfortunate impression that simulation is largely a complicated exercise in computer programming. Thus, in many simulation studies the major emphasis is erroneously on simulation software selection (see Law and Haider 1989) and on the "coding" of the simulation program.

However, based on our simulation consulting experiences during the past fourteen years, we believe that simulation modeling is actually a sophisticated systems analysis activity, and that *model coding represents only 30 to 40 percent of the total effort* in a typical sound simulation study. Even if a simulation package could be developed that made model coding time negligible, there would still be a number of substantive project issues that would have to be addressed, as discussed in the next section. Furthermore, current simulation software offers little or no assistance in these areas.

2 INGREDIENTS REQUIRED FOR SUCCESS

We have found that the following are important elements of a successful simulation project:

- Knowledge of simulation methodology, stochastic models of operations research (e.g., queueing theory), probability theory, and statistics
- Formulating the problem correctly
- Obtaining "good" information on system operating procedures and control logic
- Modeling system randomness in a reasonable manner
- Choosing appropriate simulation software and utilizing it correctly
- Establishing model validity and credibility
- Using proper statistical procedures for interpreting simulation output (classical statistical techniques for independent data are not *directly* applicable)
- Employing good project management techniques

Simulation methodology, which includes such activities as validation techniques, selecting simulation input probability distributions, and analyzing simulation output data, is taught in most university industrial engineering and management science departments. It is also available in public short courses offered by several organizations.

3 STEPS IN A SOUND SIMULATION STUDY

In Figure 1 we show the steps that will compose a typical, sound simulation study and the relationships between them. The number beside the symbol representing each step refers to the more detailed discussion of the step below. The amount of time that is required for a particular step will depend on the system being modeled; for example, there will generally be considerably more data to collect and analyze for an existing system than for a proposed one. Some simulation projects may require steps that are not depicted in the diagram. Moreover, a simulation study is not a simple sequential process. We may determine at some point in the modeling process (e.g., Steps 3 or 6) that our model is not completely "valid," which will require us to redefine our model or to collect more data (Step 2). In certain cases, we might even have to reformulate our project objectives (Step 1).

Step 1. Formulate problem and plan the study

One of the most important, but often neglected, aspects of a simulation study is a careful statement of the project's objectives. This is partly due to a lack of understanding of the nature of simulation, the information it can provide, and the time and effort required for a sound study. (We recommend that a knowledgeable simulation analyst conduct a one-hour seminar on these topics for relevant managers and engineers, if appropriate.)

It is impossible to decide upon an appropriate level of model detail without knowing precisely what issues are to be addressed by the model. We recommend that project goals be set at an initial meeting that includes managers, engineers, and operational personnel. However, one should not necessarily expect a *single* simulation model to be capable of efficiently addressing several widely disparate objectives. For example, due to computer execution time considerations, it might be necessary to use one simulation model to study the detailed workings of a particular subsystem, while another more aggregate model would be used to explore the effectiveness of the overall system.

The following tasks should be completed at the first meeting:

- Identify any performance problems for the *existing* system (if there is one)

- State definitively the study's overall objectives *and* also five to ten very specific issues to be addressed by the model

- Decide how the model will be used in the decision-making process (e.g., on a one-time basis to make capital expenditures for a new system, or to make weekly production-scheduling decisions)

- Determine who will be the model's end user (e.g., an experienced programmer/analyst versus a production engineer), since this affects how user friendly the model must be

- Specify measures of performance (e.g., mean daily throughput) that will later be used by management to compare alternative system configurations, since a model may be capable of providing an accurate estimate of one measure, but not another (see Pitfall No. 9 in Law and McComas 1989)

- Delineate the system configurations to be studied, to avoid major reprogramming later

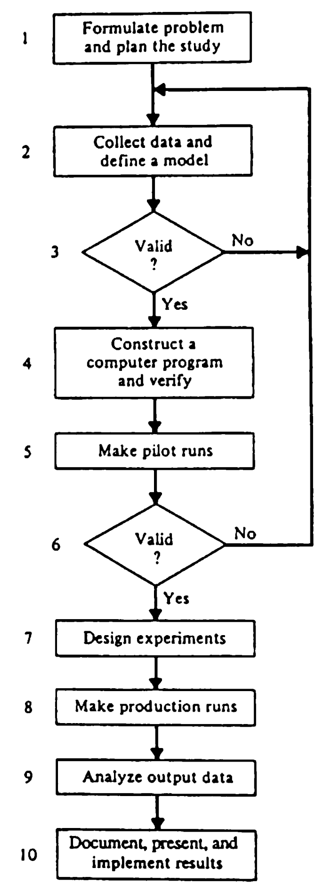

Figure 1: Steps in a simulation study

After the above initial meeting has been completed, the simulation analyst(s) should plan the overall study in terms of the number of people, the time, and the cost required for each aspect of the project. It is our experience that simulation studies often take somewhat longer than expected, due to a poor initial understanding of the complexity of the system's operating procedures.

Step 2. Collect data and define a model

The simulation analyst should collect information on system operating procedures and control logic. This will generally not be an easy task, since no single person or document will have the required information. Thus, for example, in the case of a manufacturing system the analyst might have to talk to such people as machine operators, industrial and manufacturing engineers, production planners, managers, and vendors. This process can be further complicated by inaccurate information and by the lack of formalized system operating procedures. Data should be collected (if possible) to specify model parameters (e.g., a conveyer speed) and input probability distributions (e.g., for machine operating and repair times). In general, each source of system randomness should be represented by an appropriate probability distribution (*not* just its mean) in the model (see Pitfall No. 7 in Law and McComas 1989). Furthermore, the "correctness" of each distribution should be evaluated by using graphical comparisons and statistical tests (see Law and Kelton 1991, Chapter 6 and Law and Vincent 1991).

The above information and data (in summary form) should be carefully delineated in what we call an "assumptions document" (see Law 1991). This report will typically be twenty pages in length for a manufacturing system. The assumptions document is used in the structured walk-through of the conceptual model (Step 3) and is the main documentation for the model.

Data should also be collected on the performance of the existing system (if possible) to aid in validating the model (see Step 6).

The level of model detail should depend on project objectives, data availability, credibility concerns, computer constraints, and the opinions of system "experts." For example, models used to design new systems are generally less detailed than those used to "optimize" existing systems, because of differences in project goals and in data availability. Note that it is neither necessary nor desirable to have a one-to-one correspondence between each element of the system and each element of the model.

Finally, it is extremely important for the simulation analyst to interact with the *manager* (and other key project personnel) on a regular basis *throughout the project*. This approach has the following benefits:

- Often when a study is first initiated, there is not a clear idea of the problem to be solved. Thus, as the study proceeds and the nature of the problem becomes clearer, this information should be conveyed to the manager who may reformulate the study's objectives. The greatest model for the wrong problem is clearly invalid!

- The manager's interest and involvement in the study are maintained.

- The manager's knowledge of the system contributes to the actual validity of the model.

- The model is more credible, since the manager understands and accepts the model's assumptions. (How many managers would be willing to make a million-dollar decision based on a model that they do not understand or agree with the assumptions?) As a matter of fact, it is extremely desirable to have the manager and other important personnel "sign off" on key model assumptions and to take "ownership" of the model.

Step 3. Valid?

A very important idea for validity/credibility enhancement is for the analyst to perform a structured walk-through of the conceptual model (as embodied in the assumptions document) using an overhead projector before an audience of all key people. This helps to ensure that the model's assumptions are correct, complete, and consistent (i.e., that "local" information obtained from different people is not contradictory).

At a typical structured walk-through, several erroneous model assumptions are discovered and corrected, a few new assumptions are added to the model, and some level-of-detail issues are resolved by the system "experts" present. (The assumptions document should, of course, be updated to reflect these changes.) Furthermore, at the end of the meeting, it is common for all people present to feel that they now have a valid model.

The structured walk-through should be performed before coding begins to avoid significant reprogramming if major problems are discovered at the meeting.

Step 4. Construct a computer program and verify

The choice of the software used to develop the simulation program can have a large impact on project success; it will effect the level of detail possible and, thus, model validity (if the software is not flexible enough), model execution time, and project completion time.

There are two major classes of software used for simulation modeling: *general-purpose programming languages* and *simulation packages* (or *software*). General-purpose languages (e.g., FORTRAN or C) are usually already known by the analyst, are available for all computers, and are less expensive to *purchase*. Simulation packages, on the other hand, reduce programming time significantly, provide a natural framework for simulation modeling, and typically reduce overall *project* cost. In general, we believe that it is prudent for an organization to consider the use of software designed specifically for simulation.

The two principal kinds of simulation packages are *simulation languages* and *applications-oriented simulators* (see Law and Haider 1989 for details). Simulation languages offer essentially *unlimited modeling flexibility*, but require programming expertise. Examples of simulation languages are AutoMod II, GPSS H or GPSS PC, MODSIM II, SIMAN IV, SIMSCRIPT II.5, and SLAM II.

Simulators are currently available for certain types of manufacturing, computer/communications, and airport/airspace systems. Their *goal* is to be able to construct a simulation "program" by the use of menus and graphics, without the need for programming. When simulators are applicable, they may require considerably less program development time than a simulation language. They are also easier to learn and have modeling constructs more closely related to the system of interest. *The major drawback of many simulators is that they are limited to modeling only those system configurations allowed by their standard features.* This difficulty can be partially overcome if the simulator contains "programming-like commands" to model complex decision logic or if the simulator has the ability to call routines written in a general-purpose language. (Most of the model would still be developed using menus and graphics.) Examples of simulators are COMNET II.5, LANNET II.5, NETWORK II.5, ProModel, SIMFACTORY II.5, WITNESS, and XCELL+.

We believe based on our simulation consulting experiences that most *valid* simulation models of "complex" systems *will require programming of some sort*, regardless of whether a simulation language or a simulator is used.

Most simulation software vendors offer a version of their software with *animation* capabilities. Animation is useful for communicating the essence of a simulation model (or of simulation itself) to managers and other interested persons, which increases the credibility of the model. For models with a complicated flow of entities, animation is also useful for debugging the program and finding errors in the model's logic. The following are, however, two limitations of animation:

- Animation is *not* a substitute for a careful statistical analysis of the simulation output data (Step 9)
- A "correct" animation is no guarantee of a valid or debugged model

There are a number of techniques used for debugging (also called *verifying*) the simulation program, including:

- Developing the program in a modular manner
- Using interactive debuggers and traces
- Performing a structured walk-through of the code
- Checking simulation output data for reasonableness
- Animation

Step 5. Make pilot runs

Pilot runs of the "debugged" simulation model are made for validation purposes in Step 6.

Step 6. Valid?

Numerical results and animations for the pilot runs should be reviewed carefully by system experts to detect remaining errors in the model assumptions, and the model modified to reflect any necessary changes. Note also that a realistic animation can sometimes establish credibility for a simulation model or project almost instantaneously. For example, a manager of operations at one factory, who was unfamiliar with simulation modeling, stated "That is my system!" upon seeing the animation of his production line for the first time. His interest in the simulation project was established from that time on.

Use sensitivity analyses (see Law and Kelton 1991, pp. 310-311) to determine what model aspects (e.g., an input parameter, a probability distribution, or the level of detail for a subsystem) have the greatest impact on the desired performance measures. Given that there is always only a limited amount of time and money for model development, "sensitive" aspects of the model should obviously be modeled the most carefully. For example, we used sensitivity analysis to determine the basic "unit of production" moving through a simulation model of a food packaging plant. We found that using a case of food items (approximately 500) rather than a single food item as the model unit of production did not affect the simulation results appreciably, but reduced model execution time dramatically.

The most definitive test of the validity of a simulation model is establishing that its performance measures closely approximate the performance measures that would be expected from a proposed system configuration (see Law and Kelton 1991, pp. 311-319). If a system similar to the proposed system now exists, then a pilot simulation run is made for the existing system and its output measures are compared to the corresponding measures for the existing system itself. If the two sets of measures compare "closely," then the model of the *existing system* is considered "valid." The model is then modified so that it represents the proposed system. The greater the commonality between the existing and proposed systems, the greater our confidence in the model of the proposed system. There is, however, no completely definitive approach for validating the model of the proposed system.

Step 7. Design experiments

It must be decided what system configurations to simulate, since there are sometimes more possible alternatives than one can reasonably simulate. Usually the complete decision cannot be made at this time, since the analysis of the production runs in Step 9 typically suggests additional system designs to simulate.

Since random samples from the input probability distributions "drive" a simulation model for a particular system configuration through time, basic simulation output data (e.g., daily throughputs in a factory) or an estimated performance measure computed from them (e.g., average daily throughput from the entire run) are also random. *Thus, a simulation model only produces a statistical estimate of the (true) performance measure, not the measure itself* (see Pitfall No. 10 in Law and McComas 1989). In order for a simulation estimate to be statistically precise (have a small variance) and free of bias (have mean equal to the performance measure), the analyst must specify for *each* system design appropriate choices for the following:

- Length of each simulation run
- Number of independent simulation runs
- Initial conditions for each simulation run (e.g., all machines idle and no parts present)
- Length of the warmup period, if one is appropriate

We recommend always making at least three to five independent runs for each alternative, and using the average of the estimated performance measures from the individual runs as the overall estimate of the performance measure. (Independent runs means using different random numbers for each run, starting each run in the same initial state, and resetting the model's statistical counters back to zero at the beginning of each run.) This overall estimate should be more statistically precise than the estimated performance measure from one run.

When simulating some systems (e.g., certain types of manufacturing, computer, or communication systems), we are often interested in the long-run (or steady-state) behavior of the system, i.e., its behavior when operating in a "normal" manner. On the other hand, simulations of these kinds of systems often begin with the system in an empty and idle (or some other unrepresentative) state. This results in the output data 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 *warmup period*, before the output data are actually used to estimate the desired measure of performance. Use of these warmup period data would bias the estimated performance measure.

Step 8. Make production runs

The simulation runs specified in Step 7 are executed on a computer.

Step 9. Analyze output data

The output data from the production runs are used to construct numerical estimates of the desired measures of performance for each system configuration of interest. (Confidence intervals can be used to determine the statistical precision of these estimates.) These estimated performance measures are then used to determine the efficacy of particular system designs and/or to determine the best system design relative to the specified performance measures (Step 1).

In addition to numerical estimates of the performance measures, it is often useful to employ graphical displays (histograms, pie and bar charts, time plots) of the simulation output data to gain further insights about system behavior. For example, in Figure 2 we plot total inventory (cases of product in process) as a function of time for a simulated factory. This plot provides considerable information about the dynamic characteristics of the system, such as the warmup period (the first three weeks) and the long-term cyclical nature of the inventory level (caused by the system operating procedures).

Note that the simulation results for the system designs specified in Step 7 will often suggest additional alternatives to simulate.

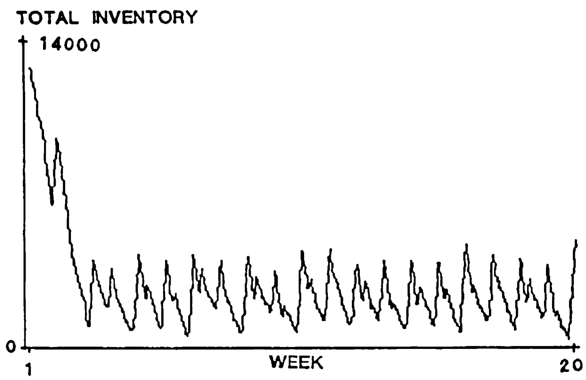

Figure 2: Plot of factory inventory level as a function of time

Step 10. Document, present, and implement results

Good documentation is very important, because simulation models are often used for more than one application. It should include an assumptions document, documentation of the program, and a report summarizing the results and conclusions of the study. The "concreteness" of the assumptions document will also enhance the credibility of the model, and make the analyst seem thorough and organized.

Most simulation projects end with a final presentation, which is often attended by people (e.g., the plant manager) who were not involved with the details of the model-building process. Thus, model credibility may have to be established for these people, and animation will certainly be useful in this regard. It is also important to discuss how information was obtained for the model and what efforts were made to validate and verify the model.

One of the most important factors in determining whether the simulation results will actually be used in the decision-making process is the credibility of the simulation model (and the analyst). This is why we have emphasized such activities as regular interaction with management, the structured walk-through of the conceptual model, and the use of animation.

4 SUMMARY

Simulation modeling is a sophisticated systems analysis activity that requires technical knowledge and project management skills to develop a model that is both valid and actually used in the decision-making process.

Organizations that are embarking on their first simulation project should probably obtain the assistance of a simulation consultant, because of the high level of expertise required and the many potential pitfalls awaiting the unwary simulation user. The consultant should not only help with the details of the project, but should also provide a technology transfer on simulation methodology.

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