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HOW TO CONDUCT A SUCCESSFUL SIMULATION STUDY

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ABSTRACT

In this tutorial we give a definitive and comprehensive seven-step approach for conducting a successful simulation study. Topics to be discussed include problem formulation, collection and analysis of data, developing a valid and credible model, modeling sources of system randomness, design and analysis of simulation experiments, and project management.

1 INTRODUCTION

A simulation study is a sophisticated systems-analysis activity that requires an analyst to have, at a minimum, knowledge of simulation methodology (model validation, selecting input probability distributions, design and analysis of simulation experiments, etc.), probability theory, statistics, project management, and the detailed operations of the system being studied. Model "programming" represents only 25 to 50 percent of the work in a sound simulation study, despite the fact that many organizations view simulation as little more than a complicated exercise in computer programming. Moreover, many of the people who perform simulation "studies" have no formal simulation training other than on the use of a particular simulation product.

In this tutorial, we give a detailed seven-step approach for conducting a successful simulation study. Many of the ideas presented here are based on Law and Kelton (2000) and on the simulation short courses presented by the author since 1977. An additional reference on the principles of simulation modeling is Banks, Carson, Nelson, and Nicol (2001).

The remainder of this paper is organized as follows. Section 2 gives definitions of important concepts for simulation modeling and Section 3 discusses a seven-step approach that incorporates these concepts. Finally, in Section 4 we discuss seventeen critical pitfalls in simulation modeling.

2 DEFINITIONS OF IMPORTANT CONCEPTS

We now discuss some important concepts that need to be addressed in any simulation study. *Verification* is concerned with determining whether the conceptual simulation model (model assumptions) has been correctly translated into a computer "program," i.e., debugging the simulation computer program. Although verification is simple in concept, debugging a large-scale simulation program is a difficult and arduous task due to the potentially large number of program paths. Techniques for debugging simulation programs include a structured-walkthrough of the program, use of a trace or an interactive debugger, and animation.

Validation is the *process* of determining whether a simulation model is an accurate representation of the system, *for the particular objectives of the study*. If a model is "valid," then it can be used to make decisions about the system similar to those that would be made if it *were* feasible and cost-effective to experiment with the system itself.

Credibility is when a simulation model and its results are accepted as "correct" by the decision-maker (or manager) and other key project personnel. Validity does not imply credibility and vice versa. For example, a valid or technically correct model might not be used in the decision-making process if the model's key assumptions are not understood and agreed with by the decision-maker. Conversely, a credible model based on an impressive three-dimensional animation might not be technically sound.

Input modeling is a statistical issue that is concerned with determining what probability distribution best represents a source of system randomness. The normal or uniform probability distributions will rarely be a good model for the time to perform some task.

Output analysis is a statistical issue that is concerned with estimating a simulation *model's* (not necessary the system's) true measures of performance. Topics of interest in output analysis include simulation run length, length of the warmup period (if any), and the number of independent model replications (using different random numbers).

3 SEVEN-STEP APPROACH FOR CONDUCTING A SUCCESSFUL SIMULATION STUDY

In Figure 1 we present a seven-step approach for conducting a successful simulation study. The activities that take place in each step are discussed in the following sections.

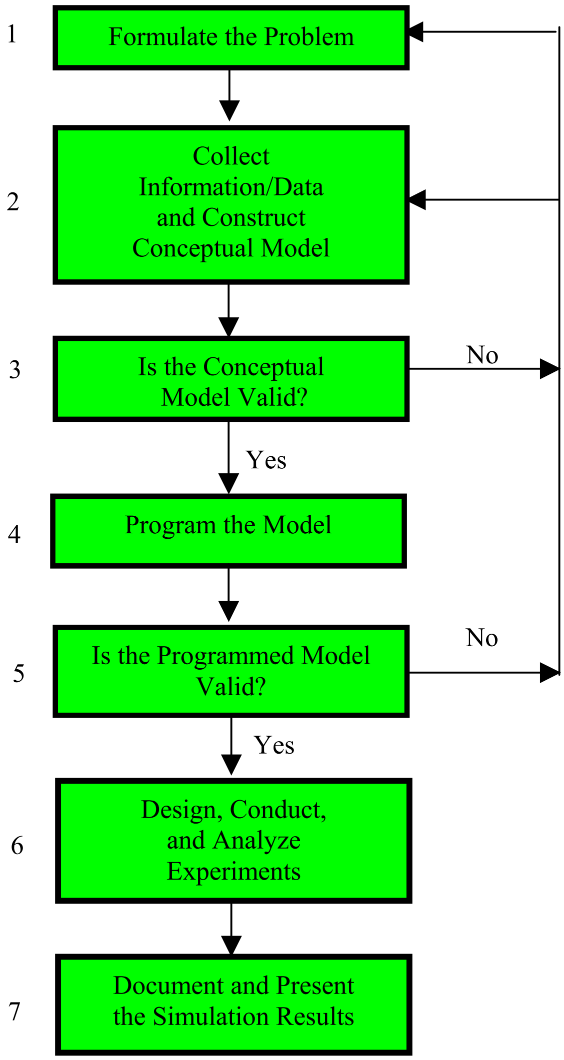

Figure 1: A Seven-Step Approach for Conducting a Successful Simulation Study

3.1 Step 1. Formulate the Problem

- The problem of interest is stated by the decision-maker. Note that when the decision-maker first initiates a simulation study, the exact problem to be solved is sometimes not precisely stated or even completely understood. Thus, as the study proceeds and a better understanding is obtained, this information should be communicated to the decision-maker who may reformulate the problem.
- A kickoff meeting(s) for the simulation project is (are) conducted, with the project manager, the simulation analysts, and subject-matter experts (SMEs) in attendance. The following things are discussed at this meeting:
  - The overall objectives of the study.
  - The *specific* questions to be answered by the study. Without such specificity, it is impossible to determine the appropriate level of model detail.
  - The performance measures that will be used to evaluate the efficacy of different system configurations. Different performance measure will sometimes dictate different levels of model detail [see Law and Kelton (2000, pp. 678-679) for an example].
  - The scope of the model.
  - The system configurations to be modeled. This information is necessary to determine the generality that must be built into the simulation computer program.
  - The time frame for the study and the required resources. Simulation projects generally take more time than originally estimated, because the system's logic turns out to be more complex than thought and because there are delays in getting the required information and data. Also, a major difficulty in many projects is the decision-maker's misunderstanding of the amount of time and resources required to perform the study.

3.2 Step 2. Collect Information/Data and Construct a Conceptual Model

- Collect information on the system structure and operating procedures.
  - No single person (or document) is sufficient. Thus, it will be necessary for the simulation analysts to talk to many different SMEs to gain a complete understanding of the system to be modeled.
  - Some of the information supplied by the SMEs will invariably be incorrect – if a certain part of the system is particularly important, then at least two SMEs should be queried.
  - System operating procedures may not be formalized.
- Collect data (if possible) to specify model parameters and probability distributions (e.g., for the time to failure and the time to repair of a machine). Two major pitfalls in this regard are replacing a probability distribution by its perceived mean value and the use of an inappropriate distribution (e.g., normal, uniform, or triangular).
- Document the model assumptions, algorithms, and data summaries in a written *conceptual model* (or "assumptions document"). This is an absolutely *critical* activity that is often skipped – verbal communication is very prone to errors. The conceptual model should include the following:
  - An overview section which contains the overall project goals, the specific issues to be addressed, and the performance measures of interest.
  - A process-flow or system-layout diagram (if appropriate).

- Detailed descriptions of each subsystem (*in bullet format* for easy review in Step 3) and how they interact.
- What simplifying assumptions were made and why. A simulation model should be a simplification or abstraction of the real system, with just enough detail to answer the questions of interest.
- Summaries of model input data – technical details and complicated mathematical/statistical calculations should be in appendices. The conceptual model should be readable by the *decision-maker* as well as by the analysts and the SMEs.
- Sources of important or controversial information, so that this information can be confirmed by an interested party.

- Collect performance data from the existing system (if any) to use for model validation in Step 5.
- The level of model detail should depend on the following:
  - Project objectives.
  - Performance measures of interest.
  - Data availability.
  - Credibility concerns – in some cases it might be necessary to put more detail into the model than would be dictated strictly from a validity point of view.
  - Computer constraints.
  - Opinions of SMEs. This is one of the most-important methods for determining what aspects of the real system impact most on performance measures of interest and, thus, have to be carefully modeled.
  - Time and money constraints.
- There should *not* be a one-to-one correspondence between each element of the model and each element of the system. Start with a "simple" model and embellish it as needed. Unnecessary model detail might result in excessive model execution time, in a missed deadline, or in obscuring those system factors that are really important.
- Interact with the decision-maker (and other key project personnel) on a regular basis, which has the following benefits:
  - Helps ensure that the correct problem is solved – the greatest model for the wrong problem will be of little value to the decision-maker.
  - The decision-maker's interest in and involvement with the study are maintained, which are very important for project success.
  - The model is more *credible* because the decision-maker understands and agrees with the model's assumptions.

3.3 Step 3. Is the Conceptual Model Valid?

- Perform a structured walk-through of the conceptual model before an audience that includes the project manager, analysts, and SMEs. This critical activity, which is called *conceptual-model validation*, is very often skipped.
  - Helps ensure that the model's assumptions are correct and complete.
  - Fosters interaction among members of the project team – having members of the project team read the conceptual model on their own is recommended but is definitely *not* sufficient.
  - Promotes ownership of the model, which can help lessen political problems.
  - Takes place *before* "programming" begins to avoid significant reprogramming later.
- If errors or omissions are discovered in the conceptual model, which is virtually always the case, then the conceptual model must be updated before proceeding to programming in Step 4.

3.4 Step 4. Program the Model

- Program the conceptual model in either a general-purpose programming language (e.g., C or C++) or in a commercial simulation-software product. Several advantages of a programming language are familiarity, greater program control, and lower *software purchase cost*. On the other hand, the use of a commercial simulation product will reduce "programming" time and *overall project cost*. There are two main types of commercial simulation-software products: general purpose (e.g., Arena, Extend, SIMUL8, and SLX) and application oriented (e.g., AutoMod, Flexsim, ProModel, SIMPROCESS, and WITNESS).
- Verify (debug) the computer program.

3.5 Step 5. Is the Programmed Model Valid?

- If there is an existing system, then compare performance measures from a simulation model of the existing system with the comparable performance measures collected from the actual existing system (see Step 2). This is called *results validation*, and is the most-important model validation technique that is available. Several real-world examples of this technique are given in Law and Kelton (2000, pp. 279-281). If results validation is successful, then it also lends credibility to the simulation model.
- Regardless of whether there is an existing system, the simulation analysts and SMEs should review the simulation results for reasonableness. If the results are consistent with how they perceive the system should operate, then the simulation model is said to have *face validity*.

- Sensitivity analyses should be performed on the programmed model to see which model factors have the greatest impact on the performance measures and, thus, have to be modeled carefully [see Law and Kelton (2000, pp. 278-279)].

3.6 Step 6. Design, Conduct, and Analyze Simulation Experiments

- For each system configuration of interest, decide on tactical issues such as simulation run length, length of the warmup period (generally necessary if the steady-state behavior of a system is of interest), and the number of independent model replications. A major pitfall here is to make one replication of the simulation model of some arbitrary length and then to assume that the resulting output statistics are, in fact, the true performance measures for the model. We recommend that a confidence interval be constructed for a performance measure of interest.
- Analyze the results and decide if additional experiments are required.

3.7 Step 7. Document and Present the Simulation Results

- The documentation for the model (and the associated simulation study) should include the conceptual model (critical for future reuse of the model, which is particularly important in the defense community where most analyses are done using legacy models), a detailed description of the computer program, and the results/conclusions for the current study.
- The final presentation for the simulation study should include animations and a discussion of the model building/validation process to promote model credibility.

4 PITFALLS IN SIMULATION MODELING

We discuss seventeen critical pitfalls in simulation modeling, which are grouped into four categories.

4.1 Modeling and Validation

- Failure to have a well-defined set of objectives at the beginning of the study
- Misunderstanding of simulation by management
- Failure to communicate with the decision-maker on a regular basis
- Failure to collect good system data
- Inappropriate level of model detail – this is one of the most common errors, particularly among new analysts
- Treating a simulation study as if it were primarily an exercise in computer programming
- Lack of knowledge of simulation methodology and also probability and statistics

4.2 Simulation Software

- Inappropriate simulation software – either too inflexible or too difficult to use
- Belief that so-called "easy-to-use software" requires a lower level of technical competence – regardless of the software used, one still has to deal with such issues as problem formulation, what data to collect, model validation, etc.
- "Blindly" using software without understanding its underlying assumptions, which might be poorly documented
- Misuse of animation – making an important decision about the system of interest based primarily on viewing an animation for a short period of time, rather than on the basis of a careful statistical analysis of the simulation output data

4.3 Modeling System Randomness

- Replacing an input probability distribution by its mean
- Incorrect choice of input probability distributions – normal or uniform distributions will rarely be correct
- Cavalier use of the triangular distribution when system data could be collected – triangular distributions cannot accurately represent a source of randomness whose density function has a long right tail, a common situation in practice

4.4 Design and Analysis of Simulation Experiments

- Misinterpretation of simulation results – treating simulation output statistics as if they were the true model performance measures
- Failure to have a warmup period when the steady-state behavior of the system is of interest
- Analyzing (correlated) output data from one replication of a simulation model using formulas that assume independence – variances might be grossly underestimated

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