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SECRETS OF SUCCESSFUL SIMULATION STUDIES

Averill M. Law

Averill M. Law & Associates, 4955 East Calle Guebabi, Tucson, USA

ABSTRACT

In this tutorial we give a definitive and comprehensive 10-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, model documentation, 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. These omissions are probably due to an analyst's education being limited to vendor training or an undergraduate course on simulation modeling that focuses on how to use a particular simulation-software package. Even if the analyst has taken a comprehensive graduate-level simulation course, there are still many opportunities for failure due to lack of real-world experience in performing simulation studies. Critical project-management ideas like the importance of a definitive problem formulation and regular interaction with the manager are typically not taught in university courses, and have to be "learned on the job." We will use the term "manager" in this paper to refer to a manager, decision-maker, or client.

In this tutorial, we give a detailed 10-step approach for conducting a successful simulation study. Many of the ideas presented here are based on Law (2024*ab*), Law (2003), and on the experiences of the 7000-8000 simulation practitioners and professors who have attended the author's short courses over the last 40+ years. An additional reference on the principles of simulation modeling is Banks et al. (2010).

The remainder of this paper is organized as follows. Section 2 gives definitions of important concepts for simulation modeling, Section 3 discusses the 10-step approach that incorporates these concepts, and Section 4 summarizes the key ideas presented in this paper.

2 DEFINITIONS OF IMPORTANT CONCEPTS

We now discuss some important and substantive concepts that need to be addressed in any sound simulation study; they are introduced here to facilitate a smooth presentation in the next section. *Verification* (see section 5.3 in Law 2024*a*) is concerned with determining whether the assumptions document (see the next page) 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 walk-through of the program, use of a trace or an interactive debugger, and animation.

Validation (see chapter 5 in Law 2024*a*) 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 (pages 153-154 in Law 2024*a*) is when a simulation model and its results are accepted as "correct" by the 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 manager. Conversely, a credible model based on an impressive three-dimensional animation might not be technically sound.

Input modeling (chapter 6 in Law 2024*a*) 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 (chapter 9 in Law 2024*a*) is a statistical issue that is concerned with estimating a simulation *model's* (not necessarily the system's) true measures of performance. Topics of interest in output analysis include simulation run length, length of the warmup period (if steady-state performance measures are of interest), and the number of independent model runs (replications) using different U(0,1) random numbers (chapter 7 in Law 2024*a*). The ability to get precise estimates of performance measures is now facilitated by fast computers with multi-core processors or the use of cloud computing.

We believe that a very important part of a sound simulation study is the documentation of model assumptions, algorithms, input parameters, performance measures, and data summaries in an *assumptions document* (section 5.4.3 in Law 2024*a*). It should be written to be readable by analysts, subject-matter experts (SMEs), and technically-trained managers alike, and contain the following:

- An overview section that discusses overall project goals, the specific issues to be addressed by the simulation study, model inputs, and the performance measures for evaluation.
- A process-flow or system-layout diagram, if appropriate.
- Detailed descriptions of each subsystem *in bullet format* and how the subsystems interact. (Bullet format, as on this page, makes the assumptions document easier to review at the structured walk-through of the assumptions document, which is described below.)
- What simplifying assumptions were made and why. Note that a simulation model is supposed to be a simplification or abstraction of reality.
- Limitations of the simulation model.
- Summaries of a data set such as its sample mean and a histogram. Detailed statistical analyses or other technical material should probably be placed in appendices to the report.
- Sources of important or controversial information (people, books, technical papers, etc.).

The assumptions document should contain enough detail so that it is a "blueprint" for creating the simulation computer program. An assumptions document is different from a *conceptual model*, which in many cases is the model developers' *initial thoughts* on the form that the model *will* take. Also, an assumptions document is *not*, in general, the same as a *requirements document*, which describes what the simulation model should be able to do. An assumptions document goes further in that it delineates in detail how the requirements will actually be met by a simulation model.

The simulation modeler will need to collect system information from many different people. Furthermore, these people are typically very busy dealing with the daily problems that occur within their organizations, often resulting in their giving something less than their undivided attention to the questions posed by the simulation modeler. As a result, there is a considerable danger that the simulation modeler will not obtain a complete and correct description of the system. One way of dealing with this potential problem is to conduct a *structured walk-through of the assumptions document* (pages 164-165 in Law 2024*a*) before an audience of analysts, SMEs, and managers. Using a projection device, the simulation modeler goes through the assumptions document bullet by bullet, but not proceeding from one bullet to the next until everybody in the room is convinced that a particular bullet is correct and at an appropriate level of detail. A structured walk-through will increase both the validity and credibility of the simulation model.

The structured walk-through should ideally be held at a remote site (e.g., a hotel meeting room) so that people give the meeting their undivided attention. Furthermore, it should be held prior to the beginning of programming in case major problems are uncovered at the meeting. The assumptions document should be sent to participants prior to the meeting and their comments requested. We do not, however, consider this to be a replacement for the structured walk-through itself, since people may not have the time or motivation to review the document on their own. Furthermore, the interactions that take place at the actual meeting are invaluable. It is imperative that all key members of the project team be present at the structured walk-through and that they take an active role. It is quite likely that *many* model assumptions will be found to be incorrect or to be missing at the structured walk-through. The errors or omissions found in the assumptions document should be corrected before programming begins.

3 TEN-STEP APPROACH FOR CONDUCTING A SUCCESSFUL SIMULATION STUDY

Figure 1 shows the steps that will compose a typical, sound simulation study. The number beside the symbol representing each step refers to the more detailed description of that step below. Note that a simulation study is not a simple sequential process. As one proceeds with the study, it may be necessary to go back to a previous step.

Step 1. Formulate the Problem and Plan the Study.

a. The problem of interest is stated by the manager. Note that when the manager first initiates the simulation study, the exact problem to be solved may not be completely understood or stated in quantitative terms. Thus, as the study proceeds and a better understanding is obtained, this information should be communicated to the manager who might reformulate the problem.

b. A kick-off meeting for the study is conducted with all stakeholders being present, including the project manager, simulation analysts, and SMEs. The following things are discussed:

- Overall objectives of the study
- *Specific* questions to be answered by the study (required to decide on an appropriate level of model detail)
- Performance measures that will be used to evaluate the efficacy of different system configurations. Different performance measures might dictate different levels of model detail.
- Scope of the model (e.g., the performance of one particular factory versus all factories owned by the company)
- System configurations to be modeled (required to decide generality of simulation program)
- Time frame for the study and the required resources (people, computers, etc.) Simulation projects generally take more time than originally estimated, because the system's logic turns out to be more complicated than expected and due to delays in getting the required information and data.

Example 1. This example demonstrates the need for item *a* in Step 1. One of my seminar attendees from a cellular phone company asked me to have dinner to discuss a potential simulation project. At dinner he drew a sketch of his system on a napkin. He then told me what his objectives were and asked me to send him a proposal. Back at my office, I started thinking about the problem, but quickly realized that I neither understood the system completely nor exactly what the objectives were. I did, however, send him a tentative proposal at his request. When he received the proposal, he said, "I'm not sure that I know what I want after all." After several more iterations, we finally came to an agreement on the system and his objectives.

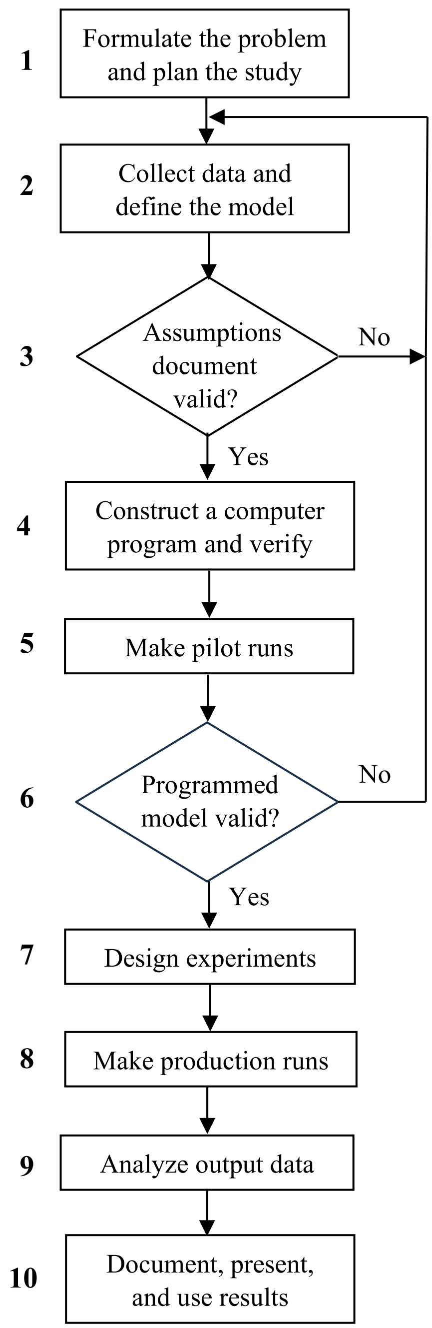

Figure 1: Steps in a simulation study.

Example 2. This example illustrates the importance of having all stakeholders present at the kick-off meeting. At the meeting for a study concerning the loading and transportation of crude oil in Alaska, the only people present were the "corporate champion" and two of us analysts. Other important stakeholders were not present due to the large geographical distances involved. As a result, the assumptions document initially had many missing and incorrect assumptions. This problem was addressed by a structured walk-though of the assumptions document as discussed in Example 8.

Step 2. **Collect Data and Define a Model.**

a. 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. Ideally, SMEs should have some knowledge of simulation modeling so that they provide relevant information and data.
- Some people may have (or provide) incorrect information – make sure that true SMEs are identified.
- System operating procedures may not be formalized.

Example 3. The maintenance department in an automotive factory exaggerated the reliability of certain machines to make themselves look good.

b. Collect data (if possible) to specify model parameters and input probability distributions (e.g., for the time to failure and time to repair of a machine). Two major pitfalls in this regard are replacing a probability distribution by its perceived mean value (due to lack of understanding by the "analyst") and the use of an inappropriate distribution such as the normal (assumes that negative values can occur, which is unlikely in most simulation applications) or uniform (assumes that every value over a range is equally likely to occur, which is implausible).

Example 4. The purpose of this example is to illustrate that the data used to build a model must be validated as well as the model logic. An oil company supplied us with 857 tanker-loading times (see Figure 2), one of which was appreciably larger than the rest (i.e., it was an *outlier*). A person who was actually involved in the loading process told us that the largest observation must have been a recording error. Thus, only the 856 smallest observations were used in our analysis.

Example 5. This example shows that the probability distribution used to model a source of system randomness can potentially have a large impact on the simulation results. A single-server queueing system (e.g., a single machine in a factory) has exponential interarrival times with a mean of 1 minute. Suppose that 200 service times are available from the system, but their underlying probability distribution is unknown. Using an approach that is discussed in section 6.5 of Law (2024*a*), we "fit" the best exponential, gamma, Weibull, lognormal, and normal distributions to the observed service-time data. We then made 100 independent simulation runs of the queueing system for *each* of the five fitted distributions. (For the normal distribution, if a service time was negative, it was generated again.) Each of the 500 simulation runs was continued until 1000 delays in queue were collected. A summary of the results from these simulation runs is given in Table 1. We performed a thorough statistical analysis of the data using graphical plots and goodness-of-fit tests, and we found that the Weibull distribution actually provided the best model for the service-time data. Thus, the average delay for the real system should be close to 4.36 minutes. Note that the use of the normal distribution would result in a 39 percent error.

c. Document the model assumptions, algorithms, input parameters, performance measures, and data summaries in a written assumptions document. This is an absolutely *critical activity* that is usually skipped – verbal communication is very prone to errors.

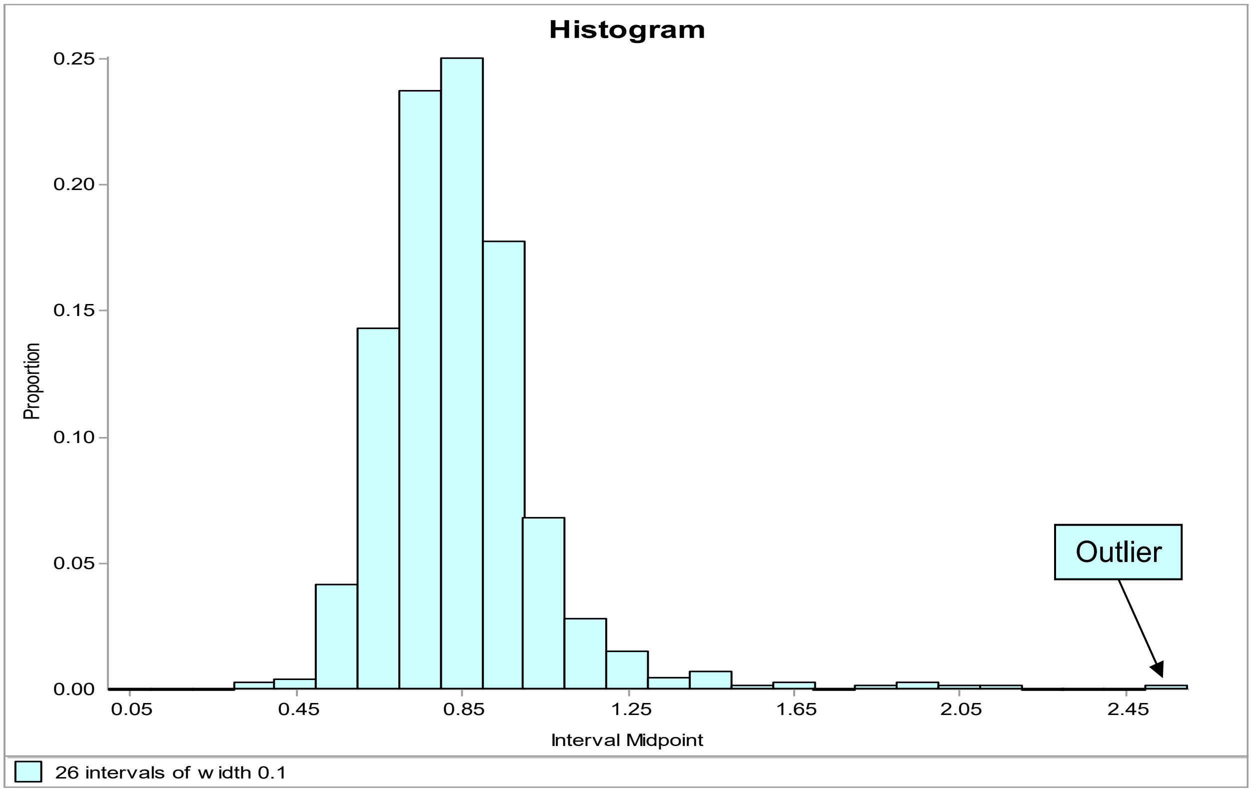

Figure 2: Histogram of 857 ship-loading times (in days).

d. Collect performance data from an existing system configuration (e.g., from a manufacturing system or from field testing a prototype weapons system) for model validation in step 6.

e. Choosing the level of model detail, which is an art, 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 (see Example 6)
- Computer constraints (less important now)
- Opinions of SMEs. This is one of the most-important methods for determining what aspects of the real system most impact on performance measures of interest and, thus, have to be modeled carefully.

Table 1: Simulation results for the five service-time distributions (in minutes).

Service-time distribution	Average delay in queue
Exponential	6.71
Gamma	4.54
Weibull	4.36
Lognormal	7.19
Normal	6.04

- Time and money constraints

Example 6. A system designed to produce pet food consisted of a meat plant and a cannery. In the meat plant, meat was either ground fine or into chunks and then placed into buckets and transported to the cannery by an overhead conveyor system. In the cannery, buckets were dumped into mixers that process the meat and then dispense it to the filler/seamers for canning. The empty buckets are conveyed back to the meat plant for refilling.

Originally, it was decided that the system producing the chunky product was relatively unimportant and, thus, it was modeled in a simple manner. However, at the structured walk-through of the model, machine operators stated that this subsystem was actually much more complex. To increase model validity and *gain credibility* with these members of the project team, we had to include machine breakdowns and contention for resources. Furthermore, after the initial runs of the model were made, it was necessary to make additional changes to the model suggested by a mixer operator. If we had not made the stated changes, members of the pet-food company would have considered the model to be invalid and not used it in the decision-making process.

f. 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. The adequacy of a particular version of the model is determined by having it reviewed by SMEs and managers. Unnecessary model details might result in an excessive model execution time, in a missed deadline, or in obscuring those system factors that are really important. Building the simplest model that provides a "valid" representation of the system is sometimes called *Occam's razor* or the *principle of parsimony*.

g. Interact with the manager (and other key project personnel) on a regular basis, which has the following benefits:

- Helps ensure that the correct problem is being solved – the greatest model for the wrong problem will be of little value to the manager.
- The manager's interest in and involvement with the study are maintained, which are very important for project success.
- The model is more *credible* because the manager understands and agrees with the model's assumptions.

Example 7. A military analyst worked on a project for months without interacting with the requesting general. At the final briefing in the U.S. Pentagon, the general walked out after five minutes stating, "That's not the problem I'm interested in."

Step 3. **Assumptions Document Valid?**

a. Perform a structured walk-through of the assumptions document before an audience of managers, analysts, and SMEs. This will

- Help ensure that the model's assumptions are correct and complete. (In fact, it is highly likely that many errors and omissions will be found!)
- Promote interaction among the project members
- Promote ownership of the model and model credibility
- Take place *before* programming begins, to avoid significant reprogramming later

Example 8. *(continuation of Example 2)* This simulation study was precipitated by the *Exxon Valdez* oil spill of 1989 that occurred in Alaska, where an oil tanker of the same name ran aground on a reef resulting in millions of gallons of crude oil being spilled and considerable harm to wildlife. As a result, the U.S. Congress passed the Oil Protection Act of 1990 that mandated that all existing tankers had to be replaced by a double-hull design by no later than 2015.

System of interest:

Crude oil was loaded onto tankers at a port in Alaska and transported down the west coast of the U.S. to refineries in the states of Washington and California. The operation of the port is greatly affected by severe weather.

Simulation study:

We were contacted by a major oil company in November 1997 to build a simulation model for determining the number of double-hulled tankers required for the system described previously. An initial estimate of the number of required tankers, which cost 200 million dollars each, was obtained by a spreadsheet analysis and a simulation model was desired for confirmation.

The assumptions document had sections corresponding to the following subsystems:

- The extraction of crude oil from the Alaskan North Slope (simplified model)
- The loading of oil onto tankers at the port
- The unloading and storage of oil at the refineries
- Nature and effect of weather
- Maintenance of tankers in Asia

Much of the information for the assumptions document was obtained from a two-day kickoff meeting in Alaska during November 1997, which involved two of us analysts and a *single* “corporate champion” from the oil company. Unfortunately, crucial SMEs were not present due to the large geographical distances involved!

Structured walk-through:

The structured walk-through took place in California during January of 1998. *Many* of the important model assumptions were found to be incorrect or missing, due to the lack of critical SMEs at the kickoff meeting. For example, it was discovered that the effect of severe weather on port operations was much more complicated than we were previously told. Also, we found out the real disposition of excess oil when a tanker arrived at a refinery with inadequate remaining storage. Namely, the excess oil was sold off to a competing company.

As a result of the disappointing structured walk-through, various SMEs at the meeting were given the responsibility of gathering information on different parts of the system, and they provided the required information to us within two weeks. The assumptions document was then updated, the simulation analysis was performed, and a second walk-through was successfully performed at the final presentation for the study. The simulation study saved the oil company 52 million dollars.

Some people think that the need for an assumption document and its formal review are just common sense. However, based on talking to literally thousands of simulation practitioners, we believe that 75 percent of simulation models have inadequate documentation.

Example 9. We were asked to help validate a simulation model for a major military weapons system, which costs billions of dollars. The model had been under development for ten years and was more than 10,000 lines of code in an outdated simulation-software package. Moreover, the documentation for the model primarily consisted of 35 large-font PowerPoint slides, making it extremely difficult to know what assumptions had been made. Although the model had been officially accredited for use, it contained a number of technical errors. For example, model task times were assumed to have no random variation.

Step 4. Construct a Computer Program and Verify.

a. Program the simulation model in a general-purpose programming language (e.g., C++, Java, or Python) or a commercial simulation-software package (e.g., AnyLogic, Arena, ExtendSim, FlexSim, Simio, or SIMUL8). Benefits of using a programming language are that one is often known, they offer greater program control, they have a low *purchase* cost or are free, and they may result in a smaller model-execution time because the model can be completely tailored to the problem at hand. The use of simulation software (chapter 3 in Law 2024*a*), on the other hand, reduces programming time because most required simulation functionality is already built-in resulting in a lower *project* cost. The choice of what software to use should be based at least partly on the requirements of the assumption document resulting from Steps 2 and 3.

b. Verify (debug) the simulation computer program.

Step 5. **Make Pilot Runs.**

a. Make pilot runs for validation purposes in step 6.

Step 6. **Programmed Model Valid?**

a. If there is an existing system, then compare model (from Step 5) and system (from step 2) output statistics (e.g., a sample mean) for the existing system (see Examples 10 and 11).

b. Whether or not there is an existing system, SMEs should review the simulation output statistics for reasonableness. If the simulation results are consistent with perceived system behavior, then the model is said to have *face validity* (see Example 12).

c. Use sensitivity analysis (pages 165-166 in Law 2024*a*) to determine what model factors have a significant impact on performance measures and, thus, have to be modeled carefully (see Example 13).

Example 10. We performed a simulation study for the corporate headquarters of a manufacturer of paper products. A particular manufacturing plant for this company currently had two machines of a certain type, and local management wanted to purchase a third machine. The goal of the study was to see whether the additional machine was really needed. To validate our model, we first simulated the existing system with two machines. The model and system throughputs for the two machines differed by 0.4 and 1.1 percent, while the machine utilizations differed by 1.7 and 11 percent. (The relatively large error of 11 percent was caused by the second machine operator's not following company policy.) Using the "validated" simulation model, we simulated the system with three machines and found that the additional machine was not necessary to meet system performance requirements. Based on the *credible* simulation results, the vice president for manufacturing of the entire company rejected the plant's request for a new machine, resulting in a capital avoidance of 1.4 million dollars.

Example 11. A U.S. Air Force test agency performed a simulation study for a wing of bombers using the Logistics Composite Model (LCOM). The goal of the study was to evaluate the effect of various proposed logistics policies on the availability of bombers, i.e., the proportion of time that bombers were available to fly missions. Data were available from the actual operations of the bomb wing over a 9-month period, and included both failure data for various aircraft components (e.g., engines and landing gear) and a bomb-wing availability of 0.9. To validate the model, the Air Force first simulated the 9-month period with the existing logistics policy and obtained a model availability of 0.873, which is 3 percent different than the historical availability. This difference was considered acceptable because an availability of 0.873 would still allow enough bombers to be available for the Air Force to meet its mission requirements.

Example 12. A simulation model was developed for the U.S. Air Force manpower and personnel system, which was designed to provide Air Force policy analysts with a systemwide view of the effects of various proposed personnel policies. The model was run under the baseline personnel policy, and the results were shown to Air Force analysts and decision-makers, who subsequently identified some discrepancies between the model and perceived system behavior. This information was used to improve the model, and after several additional evaluations and improvements, a model was obtained that appeared to approximate current Air Force policy closely. This exercise improved not only the validity of the model, but also its credibility.

Example 13. This example illustrates how sensitivity analysis was used to determine an appropriate unit of production for a manufacturing system. We built a simulation model for a candy-bar manufacturing line. Initially, we used a single candy bar as the basic entity moving through the model, but this resulted in excessive computer execution time. A sensitivity analysis was performed, and it was found that using one-quarter of a case of candy bars (150 candy bars) produced virtually the same simulation results for the desired performance measure, *cases produced per shift*, while reducing the execution time considerably.

Step 7. **Design Experiments.**

a. Specify the following for each system configuration of interest:
- Length of each simulation run
- Length of the warmup period if steady-state performance measures are of interest (pages 407-413 in Law 2024*a*)
- Number of independent simulation runs (replications) using different random numbers, which allows one to get a statistically precise estimate of the true value of a performance measure using a confidence interval.

Step 8. **Make Production Runs.**

a. Production runs of the "validated" simulation model of the system of interest are made for use in step 9.

Step 9. Analyze Output Data.

a. Two major objectives in analyzing output data are to
- Determine the absolute performance of certain system configurations (chapter 9 in Law 2024*a*).
- Compare alternative system configurations in a relative sense (chapter 10 and section 11.2 in Law 2024*a*)
- Usually, the results from simulating one or more system configurations suggest additional system configurations to be simulated.

Example 14. This example shows how dramatically simulation results can vary from one run to another because each run uses different random numbers. Consider a department of motor vehicles (DMV) with five clerks that are being fed by a single queue. The DMV is open from 9 A.M. to 5 P.M. but will serve all customers present at closing. Assume that the interarrival times are exponentially distributed with mean 1 minute and service times are exponentially distributed with mean 4.5 minutes. It can be shown from queueing theory that the long-term average utilization of the clerks is 0.9. We made 10 independent runs of the simulation with the results shown in Table 2. Note on run 1 that 494 customers were served and their average delay in queue was 10.37 minutes. On the other hand, for run 5 there were 436 customers who were served and they had an average delay in queue of 1.83 minutes, which is approximately 18 percent of what it was on run 1. Clearly, making one run of a simulation model does not produce output statistics that are the true values of the performance measures of interest. Chapter 9 of Law 2024*a* shows how to get statistically precise estimates of the true values of the performance measures.

Table 2: Results from 10 replications of the DMV.

Replication	Number of customers served	Average delay in queue
1	494	10.37
2	464	2.17
3	464	8.03
4	491	7.93
5	436	1.83
6	488	4.83
7	487	4.85
8	492	6.86
9	506	6.46
10	462	3.04

4 SUMMARY

As stated above, selecting input probability distributions, validating the model, and properly designing and analyzing simulation experiments are fundamental parts of any sound simulation study. However, it is also very important to interact with the manager on a regular basis, to develop an assumptions document, and to have it formally reviewed using a structured walk-through with all stakeholders in attendance. Unfortunately, these latter three requirements are probably not taught in most university courses and have to be learned "on the job."

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AUTHOR BIOGRAPHY

AVERILL M. LAW is President of Averill M. Law & Associates, a company specializing in simulation seminars and consulting. He has presented more than 550 simulation and statistics short courses in 20 countries, including onsite seminars for AT&T (Saudi Arabia, U.S), Australian Department of Defence, Boeing, Caterpillar, Coca-Cola, GE, GM (Canada, U.S.), IBM (Belgium, U.S.), Intel, Lockheed Martin, Los Alamos National Lab, NASA, NATO (Belgium, Netherlands), NSA, Raytheon, Sandia, Sasol Technology (South Africa), 3M, UPS, U.S. Air Force, U.S. Army (South Korea, U.S.), U.S. Navy, and Verizon. He has written or coauthored numerous papers and books on simulation, operations research, statistics, manufacturing, and communications networks, including the book *Simulation Modeling and Analysis* that has been cited more than 25,750 times and is widely considered to be the "bible" of simulation. He developed the ExpertFit® distribution-fitting software – the first commercial product of its kind – and also several videotapes on simulation modeling. He was awarded the INFORMS Simulation Society Lifetime Professional Achievement Award in 2009 for his book and the education of thousands of simulation practitioners, professors, and students through his short courses and university teaching. Dr. Law wrote a regular column on simulation for *Industrial Engineering* magazine. He has been a tenured faculty member at the University of Wisconsin-Madison and the University of Arizona, during which time his research was sponsored by the Office of Naval Research for eight years. He has a Ph.D. in industrial engineering and operations research from the University of California at Berkeley. His e-mail address is averill@simulation.ws and his website is www.averill-law.com