Part I

Introduction to Discrete-Event System Simulation

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Introduction to Simulation

A *simulation* is the imitation of the operation of a real-world process or system over time. Whether done by hand or on a computer, simulation involves the generation of an artificial history of a system and the observation of that artificial history to draw inferences concerning the operating characteristics of the real system.

The behavior of a system as it evolves over time is studied by developing a simulation *model*. This model usually takes the form of a set of assumptions concerning the operation of the system. These assumptions are expressed in mathematical, logical, and symbolic relationships between the *entities*, or objects of interest, of the system. Once developed and validated, a model can be used to investigate a wide variety of "what if" questions about the real-world system. Potential changes to the system can first be simulated, in order to predict their impact on system performance. Simulation can also be used to study systems in the design stage, before such systems are built. Thus, simulation modeling can be used both as an analysis tool for predicting the effect of changes to existing systems and as a design tool to predict the performance of new systems under varying sets of circumstances.

In some instances, a model can be developed which is simple enough to be "solved" by mathematical methods. Such solutions might be found by the use of differential calculus, probability theory, algebraic methods, or other mathematical techniques. The solution usually consists of one or more numerical parameters, which are called measures of performance of the system. However, many real-world systems are so complex that models of these systems are virtually impossible to solve mathematically. In these instances, numerical, computer-based simulation can be used to imitate the

behavior of the system over time. From the simulation, data are collected as if a real system were being observed. This simulation-generated data is used to estimate the measures of performance of the system.

This book provides an introductory treatment of the concepts and methods of one form of simulation modeling—discrete-event simulation modeling. The first chapter initially discusses when to use simulation, its advantages and disadvantages, and actual areas of its application. Then the concepts of system and model are explored. Finally, an outline is given of the steps in building and using a simulation model of a system.

1.1 When Simulation Is the Appropriate Tool

The availability of special-purpose simulation languages, of massive computing capabilities at a decreasing cost per operation, and of advances in simulation methodologies have made simulation one of the most widely used and accepted tools in operations research and systems analysis. Circumstances under which simulation is the appropriate tool to use have been discussed by many authors, from Naylor *et al*. [1966] to Shannon [1998]. Simulation can be used for the following purposes:

1. Simulation enables the study of, and experimentation with, the internal interactions of a complex system or of a subsystem within a complex system.
2. Informational, organizational, and environmental changes can be simulated, and the effect of these alterations on the model's behavior can be observed.
3. The knowledge gained during the designing of a simulation model could be of great value toward suggesting improvement in the system under investigation.
4. Changing simulation inputs and observing the resulting outputs can produce valuable insights about which variables are the most important and how variables interact.
5. Simulation can be used as a pedagogical device to reinforce analytic solution methodologies.
6. Simulation can be used to experiment with new designs or policies before implementation, so as to prepare for what might happen.
7. Simulation can be used to verify analytic solutions.
8. Simulating different capabilities for a machine can help determine its requirements.
9. Simulation models designed for training make learning possible, without the cost and disruption of on-the-job instruction.
10. Animation can show a system in simulated operation so that the plan can be visualized.
11. A modern system (factory, wafer fabrication plant, service organization, etc.) is so complex that its internal interactions can be treated only through simulation.

1.2 When Simulation Is Not Appropriate

This section is based on an article by Banks and Gibson [1997], which gives ten rules for evaluating when simulation is not appropriate. The first rule indicates that simulation should not be used when the problem can be solved by common sense. An example is given of an automobile tag facility serving customers who arrive randomly at an average rate of 100/hour and are served at a mean rate

of 12/hour. To determine the minimum number of servers needed, simulation is not necessary. Just compute $100/12 = 8.33$, which indicates that nine or more servers are needed.

The second rule says that simulation should not be used if the problem can be solved analytically. For example, under certain conditions, the average waiting time in the example above can be found using the tools described in Chapter 6 and available at `www.bcnn.net`.

The next rule says that simulation should not be used if it is less expensive to perform direct experiments. The example of a fast-food drive-in restaurant is given, where it was less expensive to stage a person taking orders using a hand-held terminal and voice communication to determine the effect of adding another order station on customer waiting time.

The fourth rule says not to use simulation if the costs exceed the savings. There are many steps in completing a simulation, as will be discussed in Section 1.12, and these must be done thoroughly. If a simulation study costs $20,000 and the savings might be $10,000, simulation would not be appropriate.

Rules five and six indicate that simulation should not be performed if the resources or time are not available. If the simulation is estimated to cost $20,000 and there is only $10,000 available, the suggestion is not to venture into a simulation study. Similarly, if a decision is needed in two weeks and a simulation would take a month, the simulation study is not advised.

Simulation takes data, sometimes lots of data. If no data is available, not even estimates, simulation is not advised. The next rule concerns the ability to verify and validate the model. If there is not enough time or if the personnel are not available, simulation is not appropriate.

If managers have unreasonable expectations, if they ask for too much too soon, or if the power of simulation is overestimated, simulation might not be appropriate.

Last, if system behavior is too complex or cannot be defined, simulation is not appropriate. Human behavior is sometimes extremely complex to model.

1.3 Advantages and Disadvantages of Simulation

Simulation is intuitively appealing to a client because it mimics what happens in a real system or what is perceived for a system that is in the design stage. The output data from a simulation should directly correspond to the outputs that could be recorded from the real system. Additionally, it is possible to develop a simulation model of a system without dubious assumptions (such as the same statistical distribution for every random variable) of mathematically solvable models. For these and other reasons, simulation is frequently the technique of choice in problem solving.

In contrast to optimization models, simulation models are "run" rather than solved. Given a particular set of input and model characteristics, the model is run and the simulated behavior is observed. This process of changing inputs and model characteristics results in a set of scenarios that are evaluated. A good solution, either in the analysis of an existing system or in the design of a new system, is then recommended for implementation.

Simulation has many advantages, but some disadvantages. These are listed by Pegden, Shannon, and Sadowski [1995]. Some advantages are these:

1. New policies, operating procedures, decision rules, information flows, organizational procedures, and so on can be explored without disrupting ongoing operations of the real system.

2. New hardware designs, physical layouts, transportation systems, and so on can be tested without committing resources for their acquisition.
3. Hypotheses about how or why certain phenomena occur can be tested for feasibility.
4. Time can be compressed or expanded to allow for a speed-up or slow-down of the phenomena under investigation.
5. Insight can be obtained about the interaction of variables.
6. Insight can be obtained about the importance of variables to the performance of the system.
7. Bottleneck analysis can be performed to discover where work in process, information, materials, and so on are being delayed excessively.
8. A simulation study can help in understanding how the system operates rather than how individuals think the system operates.
9. "What if" questions can be answered. This is particularly useful in the design of new systems.

Some disadvantages are these:

1. Model building requires special training. It is an art that is learned over time and through experience. Furthermore, if two models are constructed by different competent individuals, they might have similarities, but it is highly unlikely that they will be the same.
2. Simulation results can be difficult to interpret. Most simulation outputs are essentially random variables (they are usually based on random inputs), so it can be hard to distinguish whether an observation is the result of system interrelationships or of randomness.
3. Simulation modeling and analysis can be time consuming and expensive. Skimping on resources for modeling and analysis could result in a simulation model or analysis that is not sufficient to the task.
4. Simulation is used in some cases when an analytical solution is possible, or even preferable, as was discussed in Section 1.2. This might be particularly true in the simulation of some waiting lines where closed-form queueing models are available.

In defense of simulation, these four disadvantages, respectively, can be offset as follows:

1. Vendors of simulation software have been actively developing packages that contain models that need only input data for their operation. Such models have the generic tag "simulator" or "template."
2. Many simulation software vendors have developed output-analysis capabilities within their packages for performing very thorough analyses.
3. Simulation can be performed faster today than yesterday and will be even faster tomorrow, because of advances in hardware that permit rapid running of scenarios and because of advances in many simulation packages. For example, some simulation software contains constructs for modeling material handling that uses such transporters as fork-lift trucks, conveyors, and automated guided vehicles.
4. Closed-form models are not able to analyze most of the complex systems that are encountered in practice. During the many years of consulting practice by two of the authors, not one problem was encountered that could have been solved by a closed-form solution.

1.4 Areas of Application

The applications of simulation are vast. The Winter Simulation Conference (WSC) is an excellent way to learn more about the latest in simulation applications and theory. There are also numerous tutorials at both the beginning and advanced levels. WSC is sponsored by six technical societies and the National Institute of Standards and Technology (NIST). The technical societies are the American Statistical Association (ASA), the Association for Computing Machinery/Special Interest Group on Simulation (ACM/SIGSIM), the Institute of Electrical and Electronics Engineers: Systems, Man and Cybernetics Society (IEEE/SMCS), the Institute of Industrial Engineers (IIE), the Institute for Operations Research and the Management Sciences: Simulation Society (INFORMS-SIM), and the Society for Modeling and Simulation International (SCS). Information about the upcoming WSC can be obtained from `www.wintersim.org`. WSC programs with full papers are available from `www.informs-cs.org/wscpapers.html`. Some presentations, by area, from a recent WSC are listed next:

Manufacturing Applications
- Methodology for Selecting the Most Suitable Bottleneck Detection Method
- Automating the Development of Shipyard Manufacturing Models
- Emulation in Manufacturing Engineering Processes
- Optimized Maintenance Design for Manufacturing Performance Improvement
- Productivity Management in an Automotive-Parts Industry
- Manufacturing Line Designs in Japanese Automobile Manufacturing Plants

Wafer Fabrication
- A Paradigm Shift in Assigning Lots to Tools
- Scheduling a Multi-Chip Package Assembly Line with Reentrant Processes
- Execution Level Capacity Allocation Decisions for Assembly—Test Facilities
- Managing WIP and Cycle Time with the Help of Loop Control

Business Processing
- A New Policy for the Service Request Assignment Problem
- Process Execution Monitoring and Adjustment Schemes
- In-Store Merchandizing of Retail Stores
- Sales Forecasting for Retail Small Stores

Construction Engineering and Project Management
- Scheduling of Limited Bar-Benders over Multiple Building Sites
- Constructing Repetitive Projects
- Traffic Operations for Improved Planning of Road Construction Projects
- Template for Modeling Tunnel Shaft Construction
- Decision Support Tool for Planning Tunnel Construction

Logistics, Transportation, and Distribution
- Operating Policies for a Barge Transportation System
- Dispensing Plan for Emergency Medical Supplies in the Event of Bioterrorism

Analysis of a Complex Mail Transportation Network
Improving the Performance of Container Terminals
Yard Crane Dispatching Based on Real Time Data
Unit Loading Device Inventory in Airline Operations
Inventory Systems with Forecast Based Policy Updating
Dock Allocation in a Food Distribution Center
Operating Policies for a Barge Transportation System

Military Applications
Multinational Intra-Theatre Logistics Distribution
Examining Future Sustainability of Canadian Forces Operations
Feasibility Study for Replacing the MK19 Automatic Grenade Launching System
Training Joint Forces for Asymmetric Operations
Multi-Objective Unmanned Aerial Vehicle Mission Planning
Development of Operational Requirements Driven Federations

Health Care
Interventions to Reduce Appointment Lead-Time and Patient No-Show Rate
Supporting Smart Thinking to Improve Hospital Performance
Verification of Lean Improvement for Emergency Room Process
Reducing Emergency Department Overcrowding
Inventory Modeling of Perishable Pharmaceuticals
Implementation of an Outpatient Procedure Center
Infectious Disease Control Policy
Balancing Operating Room and Post-Anesthesia Resources
Cost Effectiveness of Colorectal Cancer Screening Tests

Additional Applications
Managing Workforce Resource Actions with Multiple Feedback Control
Analyzing the Impact of Hole-Size on Putting in Golf
Application of Particle Filters in Wildfire Spread Simulation
Predator-Prey Relationship in a Closed Habitat
Intensive Piglet Production Systems
Real-Time Delay Estimation in Call Centers
Pandemic Influenza Preparedness Plans for a Public University

For an article on the future of simulation appearing in the *ICS Newsletter* (Banks, 2008), sixteen distinguished simulationists provided their response to the following question: "What remarkable results will we observe in simulation software in the long term, say, after three years?" The responses that are shown below appeared in the referenced article:

- After new fundamental ideas and methodologies such as agent-based modeling have been adopted by the software vendors (which is going to happen within a few years), progress in simulation modeling will be driven by gains in computing power. For example, at a certain

point we will be able to simulate the detailed operation of very large supply chains and manufacturing facilities.

- Simulation modeling will be more of an "assembly" activity than a "build-from-scratch" activity. Intelligent, parameterized components will be used to piece together models rather than defining lots of detailed logic.
- Progress will be made in solving hard problems. To provide tools for really hard problems, simulation software developers will have to go back to the drawing board and seriously reconsider the fundamental question: "Who provides the power, and who provides the vision?" Getting this mix right is essential to further progress. When a software developer tries to provide both power and vision, end users are saddled with the developer's paradigms. This works well for easy problems, but poorly for hard problems. For all truly hard problems, users know more about the problems than software developers do. The obvious solution is for developers to provide well-thought-out collections of true primitives, along with ways of combining and packaging these primitives.
- Simulation software will be integrated more closely with control software.
- Modelers will have a single model that is shared across applications within the organization.
- Simulation applications will not be restricted to design applications but will also be used to make day-to-day operational decisions within an organization.
- Simulation modeling on powerful servers will be accessed with web-based interfaces.
- Better and easier modeling of human activities (e.g. embedding agent-based models into discrete-event models) will be available.
- More collaborative simulation project development can be expected.
- Interface standards and incorporation of web services allowing simulation software to not only work with each other as an integrated federation, but also standardize and simplify the way other applications interface with simulation software will be adopted.
- Analytical solving techniques (such as linear programming) will be integrated with simulation capabilities.
- The "remarkable" results will be derived from advances in other areas of computing technology and software engineering. But nothing will surpass the object-oriented paradigm that was ushered into mainstream software development by SIMULA 67, emanating from the simulation software community.

1.5 Some Recent Applications of Simulation

In this section, we present some recent applications of simulation. These have appeared in the literature indicated so you can find these cases and learn more details about them.

TITLE: "The Turkish Army Uses Simulation to Model and Optimize Its Fuel-Supply System"

AUTHOR(S): I. Sabuncuoglu, A. Hatip

REPORTED: November-December 2005 in *Interfaces*

CHALLENGE: Analysis of the Turkish army's fuel-supply system.

TECHNIQUE(S): (1) Measured performance of the existing and proposed systems under various scenarios, (2) developed a simulation optimization model based on a genetic algorithm to optimize system performance, (3) conducted extensive simulation experiments.

SAVINGS: Millions of US$.

TITLE: "PLATO Helps Athens Win Gold: Olympic Games Knowledge Modeling for Organizational Change and Resource Management"

AUTHOR(S): D.A. Beis, P. Poucopoulos, Y. Pyrgiotis, K.G. Zografos

REPORTED: January-February 2006 in *Interfaces*

CHALLENGE: Develop a systematic process for planning and designing venue operations. Develop a rich library of models that is directly transferable to future Olympic organizing committees and other sports-oriented events.

TECHNIQUE(S): Knowledge modeling and resource-management techniques and tools based on simulation and other decision analysis methodologies.

SAVINGS: Over US$69.7 million.

TITLE: "Schlumberger Uses Simulation in Bidding and Executing Land Seismic Surveys"

AUTHOR(S): P.W. Mullarkey, G. Butler, S. Gavirneni, D.J. Morrice

REPORTED: March-April 2007 in *Interfaces*

CHALLENGE: Quickly and accurately measure the cost of seismic surveys.

TECHNIQUE(S): Developed a simulation tool to evaluate the impact of crew sizes, survey area, geographical region, and weather conditions on survey costs and durations.

SAVINGS: US$1.5 to US$3.0 million annually.

TITLE: "Operations Research Helps Reshape Operations Strategy at Standard Register Company"

AUTHOR(S): S.L. Ahire, M.F. Gorman, D. Dwiggins, O. Mudry

REPORTED: November-December 2007 in *Interfaces*

CHALLENGE: Minimize the total costs to offer competitive pricing in the highly competitive traditional print market.

TECHNIQUE(S): (1) Regression to estimate costs and time attributes, (2) optimization modeling to determine the order-routing strategy, (3) simulation modeling of the production-distribution network

SAVINGS: Over US$10 million annually.

TITLE: "Simulation Implements Demand-Driven Workforce Scheduler for Service Industry"

AUTHOR(S): M. Zottolo, O.M. Ülgen, E. Williams

REPORTED: *Proceedings of the 2007 Winter Simulation Conference*, eds. S.G. Henderson, B. Biller, M.-H. Hsieh, J. Shortle, J.D. Tew, and R.R. Barton.

CONDUCTED BY: PMC (`www.pmcorp.com`)

CLIENT: Major US appliance company.

CHALLENGE: As a result of a time-consuming, manual, and inefficient scheduling process the client was experiencing over- and underscheduling of workgroups, inconsistent service levels being provided, and overwhelmed site managers.

TECHNIQUE(S): (1) Built simulation model to schedule different workgroups according to changes in customer demand during the day and servicing times, (2) determined work standards, (3) developed interface for input data as well as storing and publishing of schedules, (4) implemented and trained employees on the use of the scheduling tool.

SAVINGS: Estimated at US$80 million for client's US facilities.

TITLE: "Simulation Improves End-of-Line Sortation and Material Handling Pickup Scheduling at Appliance Manufacturer"

AUTHOR(S): N. Kale, M. Zottolo, O.M. Ülgen, E. Williams

CONDUCTED BY: PMC (`www.pmcorp.com`)

CLIENT: Major US car rental company.

REPORTED: *Proceedings of the 2007 Winter Simulation Conference*, eds. S.G. Henderson, B. Biller, M.-H. Hsieh, J. Shortle, J.D. Tew, and R.R. Barton.

CHALLENGE: To determine the most efficient method to distribute several types of finished appliances (SKUs) into a 12-lane sortation system in order to minimize the material handling and the number of forklifts required to pick them. This sortation task and its associated material-handling tasks were of a complexity meriting discrete-event simulation analysis due to volatile product mix, the large number of SKUs, and high overhead costs.

TECHNIQUE(S): Built simulation model and performed experimentation with respect to (1) assignment of different SKUs to the different lanes, (2) picking strategy and quantity, (3) SKU batch sizes.

SAVINGS: Estimated US$100,000 annually for a US$50,000 one-time capital investment.

1.6 Systems and System Environment

To model a system, it is necessary to understand the concept of a system and the system boundary. A *system* is defined as a group of objects that are joined together in some regular interaction or interdependence toward the accomplishment of some purpose. An example is a production system manufacturing automobiles. The machines, component parts, and workers operate jointly along an assembly line to produce a high-quality vehicle.

A system is often affected by changes occurring outside the system. Such changes are said to occur in the *system environment* [Gordon, 1978]. In modeling systems, it is necessary to decide on the *boundary* between the system and its environment. This decision may depend on the purpose of the study.

In the case of the factory system, for example, the factors controlling the arrival of orders may be considered to be outside the influence of the factory and therefore part of the environment. However, if the effect of supply on demand is to be considered, there will be a relationship between factory output and arrival of orders, and this relationship must be considered an activity of the system. Similarly, in the case of a bank system, there could be a limit on the maximum interest rate that can be paid. For the study of a single bank, this would be regarded as a constraint imposed by the environment. In a study of the effects of monetary laws on the banking industry, however, the setting of the limit would be an activity of the system [Gordon, 1978].

1.7 Components of a System

In order to understand and analyze a system, a number of terms need to be defined. An *entity* is an object of interest in the system. An *attribute* is a property of an entity. An *activity* represents a time period of specified length. If a bank is being studied, customers might be one of the entities, the balance in their checking accounts might be an attribute, and making deposits might be an activity.

The collection of entities that compose a system for one study might only be a subset of the overall system for another study [Law, 2007]. For example, if the aforementioned bank is being studied to determine the number of tellers needed to provide for paying and receiving, the system can be defined as that portion of the bank consisting of the regular tellers and the customers waiting in line. If the purpose of the study is expanded to determine the number of special tellers needed (to prepare cashier's checks, to conduct commercial transactions, etc.), the definition of the system must be expanded.

The *state* of a system is defined to be that collection of variables necessary to describe the system at any time, relative to the objectives of the study. In the study of a bank, possible state variables are the number of busy tellers, the number of customers waiting in line or being served, and the arrival time of the next customer. An *event* is defined as an instantaneous occurrence that might change the state of the system. The term *endogenous* is used to describe activities and events occurring within a system, and the term *exogenous* is used to describe activities and events in the environment that affect the system. In the bank study, the arrival of a customer is an exogenous event, and the completion of service of a customer is an endogenous event.

Table 1.1 lists examples of entities, attributes, activities, events, and state variables for several systems. Only a partial listing of the system components is shown. A complete list cannot be

Table 1.1 Examples of Systems and Their Components

System	*Entities*	*Attributes*	*Activities*	*Events*	*State Variables*
Banking	Customers	Checking-account balance	Making deposits	Arrival; departure	Number of busy tellers; number of customers waiting
Rapid rail	Riders	Origin; destination	Traveling	Arrival at station; arrival at destination	Number of riders waiting at each station; number of riders in transit
Production	Machines	Speed; capacity; breakdown rate	Welding; stamping	Breakdown	Status of machines (busy, idle, or down)
Communications	Messages	Length; destination	Transmitting	Arrival at destination	Number waiting to be transmitted
Inventory	Warehouse	Capacity	Withdrawing	Demand	Levels of inventory; backlogged demands

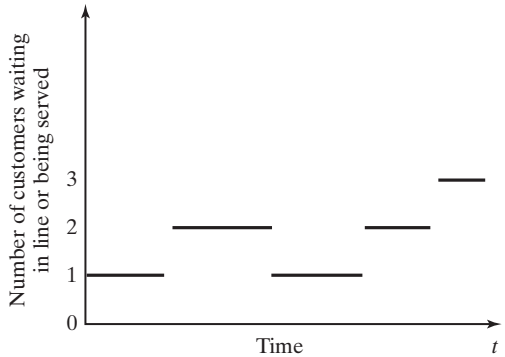

Figure 1.1 Discrete-system state variable.

developed unless the purpose of the study is known. Depending on the purpose, various aspects of the system will be of interest, and then the listing of components can be completed.

1.8 Discrete and Continuous Systems

Systems can be categorized as discrete or continuous. "Few systems in practice are wholly discrete or continuous, but since one type of change predominates for most systems, it will usually be possible to classify a system as being either discrete or continuous" [Law, 2007]. A *discrete system* is one in which the state variable(s) change only at a discrete set of points in time. The bank is an example of a discrete system: The state variable, the number of customers in the bank, changes only when a customer arrives or when the service provided a customer is completed. Figure 1.1 shows how the number of customers changes only at discrete points in time.

A *continuous system* is one in which the state variable(s) change continuously over time. An example is the head of water behind a dam. During and for some time after a rain storm, water flows into the lake behind the dam. Water is drawn from the dam for flood control and to make electricity. Evaporation also decreases the water level. Figure 1.2 shows how the state variable *head of water behind the dam* changes for this continuous system.

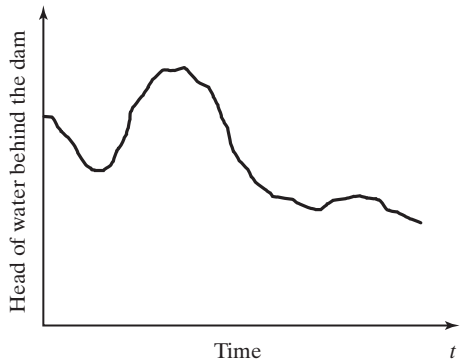

Figure 1.2 Continuous-system state variable.

1.9 Model of a System

Sometimes it is of interest to study a system to understand the relationships between its components or to predict how the system will operate under a new policy. To study the system, it is sometimes possible to experiment with the system itself. However, this is not always an option. A new system might not yet exist; it could be in only hypothetical form or at the design stage. Even if the system exists, it might be impractical to experiment with it. For example, it might not be wise or possible to double the unemployment rate to discover the effect of employment on inflation. In the case of a bank, reducing the numbers of tellers to study the effect on the length of waiting lines might infuriate the customers so greatly that they will move their accounts to a competitor. Consequently, studies of systems are often accomplished with a model of a system.

We had a consulting job for the simulation of a redesigned port in Western Australia. At US$200 million for a loading/unloading berth, it is not advisable to invest that amount only to find that the berth is inadequate for the task.

A *model* is defined as a representation of a system for the purpose of studying that system. For most studies, it is only necessary to consider those aspects of the system that affect the problem under investigation. These aspects are represented in a model of the system; the model, by definition, is a simplification of the system. On the other hand, the model should be sufficiently detailed to permit valid conclusions to be drawn about the real system. Different models of the same system could be required as the purpose of investigation changes.

Just as the components of a system include entities, attributes, and activities, so too models are represented. However, the model contains only those components that are relevant to the study. The components of a model are discussed more extensively in Chapter 3.

1.10 Types of Models

Models can be classified as being mathematical or physical. A mathematical model uses symbolic notation and mathematical equations to represent a system. A simulation model is a particular type of mathematical model of a system. A physical model is a larger or smaller version of an object such as the enlargement of an atom or a scaled-down version of the solar system.

Simulation models may be further classified as being static or dynamic, deterministic or stochastic, and discrete or continuous. A *static* simulation model, sometimes called a Monte Carlo simulation, represents a system at a particular point in time. *Dynamic* simulation models represent systems as they change over time. The simulation of a bank from 9:00 A.M. to 4:00 P.M. is an example of a dynamic simulation.

Simulation models that contain no random variables are classified as *deterministic*. Deterministic models have a known set of inputs, that will result in a unique set of outputs. Deterministic arrivals would occur at a dentist's office if all patients arrived at their scheduled appointment times. A *stochastic* simulation model has one or more random variables as inputs. Random inputs lead to random outputs. Since the outputs are random, they can be considered only as estimates of the true characteristics of a model. The simulation of a bank would usually involve random interarrival times and random service times. Thus, in a stochastic simulation, the output measures—the average number of people waiting, the average waiting time of a customer—must be treated as statistical estimates of the true characteristics of the system.

Discrete and continuous systems were defined in Section 1.7. Discrete and continuous models are defined in an analogous manner. However, a discrete simulation model is not always used to model a discrete system, nor is a continuous simulation model always used to model a continuous system. Tanks and pipes might be modeled discretely, even though we know that fluid flow is continuous. In addition, simulation models may be mixed, both discrete and continuous. The choice of whether to use a discrete or continuous (or both discrete and continuous) simulation model is a function of the characteristics of the system and the objective of the study. Thus, a communication channel could be modeled discretely if the characteristics and movement of each message were deemed important. Conversely, if the flow of messages in aggregate over the channel were of importance, modeling the system via continuous simulation could be more appropriate. The models emphasized in this text are dynamic, stochastic, and discrete.

1.11 Discrete-Event System Simulation

This is a textbook about discrete-event system simulation. Discrete-event system simulation is the modeling of systems in which the state variable changes only at a discrete set of points in time. The simulation models are analyzed by numerical rather than analytical methods. *Analytical* methods employ the deductive reasoning of mathematics to "solve" the model. For example, differential calculus can be used to compute the minimum-cost policy for some inventory models. *Numerical* methods employ computational procedures to "solve" mathematical models. In the case of simulation models, which employ numerical methods, models are "run" rather than solved—that is, an artificial history of the system is generated from the model assumptions, and observations are collected to be analyzed and to estimate the true system performance measures. Real-world simulation models are rather large, and the amount of data stored and manipulated is vast, so such runs are usually conducted with the aid of a computer. However, much insight can be obtained by simulating small models manually.

In summary, this textbook is about discrete-event system simulation in which the models of interest are analyzed numerically, usually with the aid of a computer.

1.12 Steps in a Simulation Study

Figure 1.3 shows a set of steps to guide a model builder in a thorough and sound simulation study. Similar figures and discussion of steps can be found in other sources [Shannon, 1975; Gordon, 1978; Law, 2007]. The number beside each symbol in Figure 1.3 refers to the more detailed discussion in the text. The steps in a simulation study are as follows:

1. Problem formulation Every study should begin with a statement of the problem. If the statement is provided by the policymakers or those that have the problem, the analyst must ensure that the problem being described is clearly understood. If a problem statement is being developed by the analyst, it is important that the policymakers understand and agree with the formulation. Although not shown in Figure 1.3, there are occasions where the problem must be reformulated as the study progresses. In many instances, policymakers and analysts are aware that there is a problem long before the nature of the problem is known.

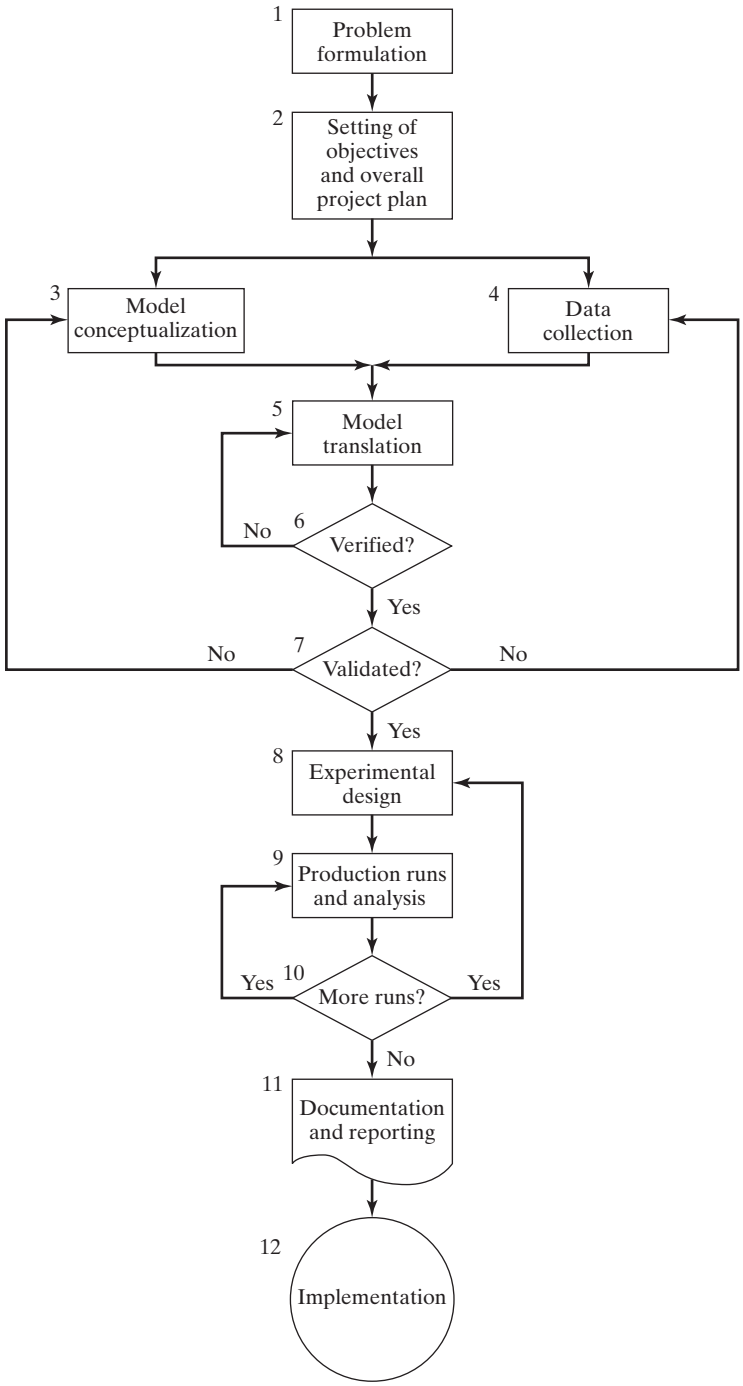

Figure 1.3 Steps in a simulation study.

2. Setting of objectives and overall project plan The objectives indicate the questions to be answered by simulation. At this point, a determination should be made concerning whether simulation is the appropriate methodology for the problem as formulated and the objectives as stated. Assuming that it is decided that simulation is appropriate, the overall project plan should include a statement of the alternative systems to be considered and of a method for evaluating the effectiveness of these alternatives. It should also include the plans for the study in terms of the number of people involved, the cost of the study, and the number of days required to accomplish each phase of the work, along with the results expected at the end of each stage.

3. Model conceptualization The construction of a model of a system is probably as much art as science. Pritsker [1998] provides a lengthy discussion of this step. "Although it is not possible to provide a set of instructions that will lead to building successful and appropriate models in every instance, there are some general guidelines that can be followed" [Morris, 1967]. The art of modeling is enhanced by an ability to abstract the essential features of a problem, to select and modify basic assumptions that characterize the system, and then to enrich and elaborate the model until a useful approximation results. Thus, it is best to start with a simple model and build toward greater complexity. However, the model complexity need not exceed that required to accomplish the purposes for which the model is intended. Violation of this principle will only add to model-building and computer expenses. It is not necessary to have a one-to-one mapping between the model and the real system. Only the essence of the real system is needed.

It is advisable to involve the model user in model conceptualization. Involving the model user will both enhance the quality of the resulting model and increase the confidence of the model user in the application of the model. (Chapter 2 describes a number of simulation models. Chapter 6 describes queueing models that can be solved analytically. However, only experience with real systems—versus textbook problems—can "teach" the art of model building.)

4. Data collection There is a constant interplay between the construction of the model and the collection of the needed input data [Shannon, 1975]. As the complexity of the model changes, the required data elements can also change. Also, since data collection takes such a large portion of the total time required to perform a simulation, it is necessary to begin as early as possible, usually together with the early stages of model building.

The objectives of the study dictate, in a large way, the kind of data to be collected. In the study of a bank, for example, if the desire is to learn about the length of waiting lines as the number of tellers changes, the types of data needed would be the distributions of interarrival times (at different times of the day), the service-time distributions for the tellers, and historic distributions on the lengths of waiting lines under varying conditions. This last type of data will be used to validate the simulation model. (Chapter 9 discusses data collection and data analysis; Chapter 5 discusses statistical distributions that occur frequently in simulation modeling. See also an excellent discussion by Henderson [2003].)

5. Model translation Most real-world systems result in models that require a great deal of information storage and computation, so the model must be entered into a computer-recognizable format. We use the term *program* even though it is possible, in many instances, to accomplish the desired result with little or no actual coding. The modeler must decide whether to program the model in a simulation language, such as GPSS/H (discussed in Chapter 4), or to use special-purpose

simulation software. For manufacturing and material handling, Chapter 4 discusses such software as AnyLogic®, Arena®, AutoMod™, Enterprise Dynamics®, Extend™, Flexsim, ProModel®, and SIMUL8®. Simulation languages are powerful and flexible. However, if the problem is amenable to solution with the simulation software, the model development time is greatly reduced. Furthermore, most simulation software packages have added features that enhance their flexibility, although the amount of flexibility varies greatly.

6. Verified? Verification pertains to the computer program that has been prepared for the simulation model. Is the computer program performing properly? With complex models, it is difficult, if not impossible, to translate a model successfully in its entirety without a good deal of debugging; if the input parameters and logical structure of the model are correctly represented in the computer, verification has been completed. For the most part, common sense is used in completing this step. (Chapter 10 discusses verification of simulation models, and Sargent [2007] also discusses this topic.)

7. Validated? Validation usually is achieved through the calibration of the model, an iterative process of comparing the model against actual system behavior and using the discrepancies between the two, and the insights gained, to improve the model. This process is repeated until model accuracy is judged acceptable. In the previously mentioned example of a bank, data was collected concerning the length of waiting lines under current conditions. Does the simulation model replicate this system measure? This is one means of validation. (Chapter 10 discusses the validation of simulation models, and Sargent [2007] also discusses this topic.)

8. Experimental design The alternatives that are to be simulated must be determined. Often, the decision concerning which alternatives to simulate will be a function of runs that have been completed and analyzed. For each system design that is simulated, decisions need to be made concerning the length of the initialization period, the length of simulation runs, and the number of replications to be made of each run. (Chapters 11 and 12 discuss issues associated with the experimental design, and Sanchez [2007] discusses this topic extensively.)

9. Production runs and analysis Production runs and their subsequent analysis, are used to estimate measures of performance for the system designs that are being simulated. (Chapters 11 and 12 discuss the analysis of simulation experiments, and Chapter 4 discusses software to aid in this step, including AutoStat (in AutoMod), OptQuest (in several pieces of simulation software), and SimRunner (in ProModel).

10. More runs? Given the analysis of runs that have been completed, the analyst determines whether additional runs are needed and what design those additional experiments should follow.

11. Documentation and reporting There are two types of documentation: program and progress. Program documentation is necessary for numerous reasons. If the program is going to be used again by the same or different analysts, it could be necessary to understand how the program operates. This will create confidence in the program, so that model users and policymakers can make decisions based on the analysis. Also, if the program is to be modified by the same or a

different analyst, this step can be greatly facilitated by adequate documentation. One experience with an inadequately documented program is usually enough to convince an analyst of the necessity of this important step. Another reason for documenting a program is so that model users can change parameters at will in an effort to learn the relationships between input parameters and output measures of performance or to discover the input parameters that "optimize" some output measure of performance.

Musselman [1998] discusses progress reports that provide the important, written history of a simulation project. Project reports give a chronology of work done and decisions made. This can prove to be of great value in keeping the project on course. Musselman suggests frequent reports (monthly, at least) so that even those not involved in the day-to-day operation can be kept abreast. The awareness of these others can often enhance the successful completion of the project by surfacing misunderstandings early, when the problem can be solved easily. Musselman also suggests maintaining a project log to provide a comprehensive record of accomplishments, change requests, key decisions, and other items of importance.

On the reporting side, Musselman suggests frequent deliverables. These may or may not be the results of major accomplishments. His maxim is that "it is better to work with many intermediate milestones than with one absolute deadline." Possibilities prior to the final report include a model specification, prototype demonstrations, animations, training results, intermediate analyses, program documentation, progress reports, and presentations. He suggests that these deliverables should be timed judiciously over the life of the project.

The results of all the analysis should be reported clearly and concisely in a final report. This will allow the model users (now the decision makers) to review the final formulation, the alternative systems that were addressed, the criteria by which the alternatives were compared, the results of the experiments, and the recommended solution(s) to the problem. Furthermore, if decisions have to be justified at a higher level, the final report should provide a vehicle of certification for the model user/decision maker and add to the credibility of the model and of the model-building process.

12. Implementation The success of the implementation phase depends on how well the previous eleven steps have been performed. It is also contingent upon how thoroughly the analyst has involved the ultimate model user during the entire simulation process. If the model user has been involved during the entire model-building process and if the model user understands the nature of the model and its outputs, the likelihood of a vigorous implementation is enhanced [Pritsker, 1995]. Conversely, if the model and its underlying assumptions have not been properly communicated, implementation will probably suffer, regardless of the simulation model's validity.

The simulation-model building process shown in Figure 1.3 can be broken down into four phases. The first phase, consisting of steps 1 (Problem formulation) and 2 (Setting of objective and overall design), is a period of discovery or orientation. The initial statement of the problem is usually quite "fuzzy," the initial objectives will usually have to be reset, and the original project plan will usually have to be fine-tuned. These recalibrations and clarifications could occur in this phase or perhaps will occur after or during another phase (i.e., the analyst might have to restart the process).

The second phase is related to model building and data collection and includes steps 3 (Model conceptualization), 4 (Data collection), 5 (Model translation), 6 (Verification), and 7 (Validation). A continuing interplay is required among the steps. Exclusion of the model user during this phase can have dire implications at the time of implementation.

The third phase concerns the running of the model. It involves steps 8 (Experimental design), 9 (Production runs and analysis), and 10 (More runs). This phase must have a comprehensively conceived plan for experimenting with the simulation model. A discrete-event stochastic simulation is, in fact, a statistical experiment. The output variables are estimates that contain random error, and therefore a proper statistical analysis is required. Such a philosophy is in contrast to that of the analyst who makes a single run and draws an inference from that single data point.

The fourth phase, implementation, involves steps 11 (Documentation and reporting) and 12 (Implementation). Successful implementation depends on continual involvement of the model user and on the successful completion of every step in the process. Perhaps the most crucial point in the entire process is Step 7 (Validation), because an invalid model is going to lead to erroneous results, which, if implemented, could be dangerous, costly, or both.

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EXERCISES

1. Name several entities, attributes, activities, events, and state variables for the following systems:
   (a) A cafeteria
   (b) A grocery store
   (c) A laundromat
   (d) A fast-food restaurant
   (e) A hospital emergency room
   (f) A taxicab company with 10 taxis
   (g) An automobile assembly line

2. Consider the simulation process shown in Figure 1.3.
   (a) Reduce the steps by at least two by combining similar activities. Give your rationale.
   (b) Increase the steps by at least two by separating current steps or enlarging on existing steps. Give your rationale.

3. A simulation of a major traffic intersection is to be conducted, with the objective of improving the current traffic flow. Provide three iterations, in increasing order of complexity, of steps 1 and 2 in the simulation process of Figure 1.3.

4. A simulation is to be conducted of cooking a spaghetti dinner, to discover at what time a person should start in order to have the meal on the table by 7:00 P.M. Download a recipe from the web for preparing a spaghetti dinner (or ask a friend or relative for the recipe). As best you can, trace what you understand to be needed, in the data-collection phase of the simulation process of Figure 1.3, in order to perform a simulation in which the model includes each step in the recipe. What are the events, activities, and state variables in this system?

5. What are the events and activities associated with the use of your checkbook?

6. Numerous reasons for simulation were given in Section 1.1. But there may be other reasons. Look at applications in the current *WSC Proceedings* and see if you can discover additional reasons. (*WSC Proceedings* are found at `www.informs-cs.org/wscpapers.html`)

7. In the current *WSC Proceedings* available at `www.informs-cs.org/wscpapers.html`, read an article on the application of simulation related to your major area of study or interest, and prepare a report on how the author accomplishes the steps given in Figure 1.3.

8. Get a copy of a recent *WSC Proceedings* from the URL in Exercise 7 and report on the different applications discussed in an area of interest to you.

9. Get a copy of a recent *WSC Proceedings* from the URL in Exercise 7 and report on the most unusual application that you can find.

10. Locate one of the cases in Section 1.12 and describe the methodology used.

11. Go to the Winter Simulation Conference website at `www.wintersim.org` and address the following:

    (a) What advanced tutorials were offered at the previous WSC or are planned at the next WSC?
    (b) Where and when will the next WSC be held?

12. Go to the Winter Simulation Conference website at `www.wintersim.org` and address the following:

    (a) When was the largest (in attendance) WSC, and how many attended?
    (b) In what calendar year, from the beginning of WSC, was there no conference?
    (c) What was the largest expanse of time, from the beginning of WSC, between occurrences of the Conference?
    (d) Beginning with the 25th WSC, can you discern a pattern for the location of the conference?

13. What is the procedure for contributing a paper to the WSC?

14. Classify the list of vendors at a recent WSC as software vendors and others.

15. What is the purpose and history of the WSC Foundation?

16. Using your favorite search engine, search the web for 'discrete event simulation output analysis' and prepare a report discussing what you find.

17. Using your favorite search engine, search the web for 'supply chain simulation' and prepare a report discussing what you find.

18. Using your favorite search engine, search the web for 'web based simulation' and prepare a report discussing what you find.