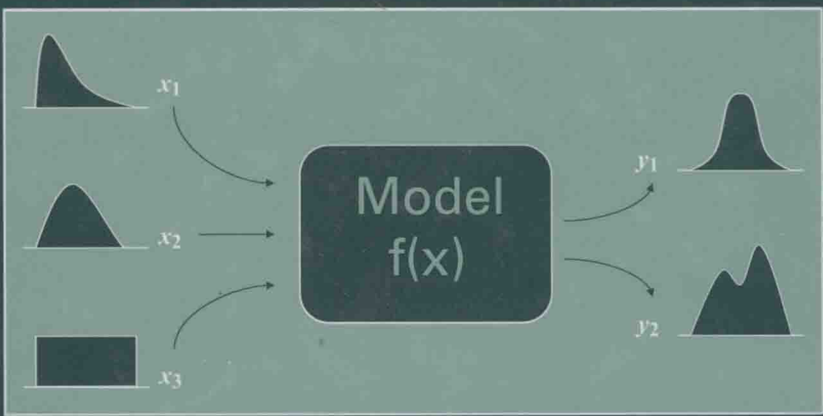
Modeling and Simulation Fundamentals

Theoretical Underpinnings and Practical Domains



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Theoretical Underpinnings and Practical Domains

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This book is dedicated to

my mom, in her memory
–John A. Sokolowski

my father, who is always in my thoughts
–Catherine M. Banks

PREFACE

Modeling and simulation (M&S) has evolved from tool to discipline in less than two decades. With the technology boom of the 1990s came the ability to use models and simulations in nearly every aspect of life. What was once a tool for training the military (war-gaming) is now a capability to better understand human behavior, enterprise systems, disease proliferation, and so much more. To equip developers of M&S, the theoretical underpinnings must be understood. To prepare users of M&S, practical domains must be explored. The impetus for this book is to provide students of M&S with a study of the discipline a survey at a high-level overview.

The purpose of the text is to provide a study that includes definitions, paradigms, applications, and subdisciplines as a way of orienting students to M&S as a discipline and to its body of knowledge. The text will provide general conceptual framework for further MSIM studies.

To students who will be reading this text, we offer an incisive analysis of the key concepts, body of knowledge, and application of M&S. This text is designed for graduate students with engineering, mathematical, and/or computer science undergraduate training for they must have proficiency with mathematical representations and computer programs.

The text is divided into 12 chapters that build from topic to topic to provide the foundation/theoretical underpinnings to M&S and then progress to applications/practical domains. Chapter 1, "Introduction to Modeling and Simulation," provides a brief history, terminology, and applications and domains of M&S. Chapter 2, "Statistical Concepts for Discrete Event Simulation," provides the mathematical background. Chapters 3 to 5 develop a three-part series of M&S paradigms, starting with Chapter 3, "Discrete-Event Simulation," Chapter 4, "Modeling Continuous Systems," and Chapter 5, "Monte Carlo Simulation." Chapters 6 and 7 develop two areas necessary for model development. Chapter 6, "Systems Modeling: Analysis and Operations Research," reviews model types and research methods, and Chapter 7, "Visualization," brings into the discussion the importance of graphics.

The next four chapters cover sophisticated methodologies, verification and validation, and advanced simulation techniques: Chapter 8, "M&S Methodologies: A Systems Approach to the Social Sciences," Chapter 9, "Modeling Human Behavior," Chapter 10, "Verification, Validation, and Accreditation," and Chapter 11, "An Introduction to Distributed Simulation." The concluding chapter, "Interoperability and Composability," introduces the importance of interoperability for engaging M&S within a number of domains.

While figures in the book are not printed in color, some chapters have figures that are described using color. The color representations of these figures may be downloaded from the following site: ftp://ftp.wiley.com/public/sci_tech_med/modeling_simulation.

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CONTENTS

1

INTRODUCTION TO MODELING AND SIMULATION

Catherine M. Banks

Modeling and simulation (M&S) is becoming an academic program of choice for science and engineering students in campuses across the country. As a discipline, it has its own body of knowledge, theory, and research methodology. Some in the M&S community consider it to be an infrastructure discipline necessary to support integration of the partial knowledge of other disciplines needed in applications. Its robust theory is based on dynamic systems, computer science, and an ontology of the domain. Theory and ontology characterize M&S as distinct in relation to other disciplines; these serve as necessary components of a body of knowledge needed to practice M&S professionally in any of its aspects.

At the core of the discipline of M&S is the fundamental notion that *models are approximations of the real world*. This is the first step in M&S, creating a model approximating an event or a system. In turn, the model can then be modified in which *simulation* allows for the repeated observation of the model. After one or many simulations of the model, *analysis* takes place to draw conclusions, verify and validate the research, and make recommendations based on various simulations of the model. As a way of representing data, *visualization* serves to interface with the model. Thus, M&S is a problem-based discipline that allows for repeated testing of a hypothesis. Significantly, M&S

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expands the capacity to analyze and communicate new research or findings. This makes M&S unique to other methods of research and development.

Accordingly, the intent of this text is to introduce students to the fundamentals, the theoretical underpinnings, and practical domains of M&S as a discipline. An understanding and application of these skills will prepare M&S professionals to engage this critical technology.

M&S

The foundation of an M&S program of study is its curriculum built upon four precepts—modeling, simulation, visualization, and analysis. The discussion below is a detailed examination of these precepts as well as other terms integral to M&S.* A good place to start is to define some principal concepts like system, model, simulation, and M&S.

Definition of Basic Terms and Concepts

Because system can mean different things across the disciplines, an agreed upon definition of system was developed by the International Council of Systems Engineering (INCOSE). INCOSE suggests that a *system* is a construct or collection of different elements that together produces results not obtainable by the elements alone.** The elements can include people, hardware, software, facilities, policies, documents—all things required to produce system-level qualities, properties, characteristics, functions, behavior, and performance. Importantly, the value of the system as a whole is the relationship among the parts. A system may be *physical*, something that already exists, or *notional*, a plan or concept for something physical that does not exist.

In M&S, the term system refers to the subject of model development; that is, it is the subject or thing that will be investigated or studied using M&S. When investigating a system, a quantitative assessment is of interest to the modeler—observing how the system performs with various inputs and in different environments. Of importance is a quantitative evaluation of the performance of the system with respect to some specific criteria or performance measure. There are two types of systems: (1) *discrete*, in which the state variables (variables that completely describe a system at any given moment in time) change instantaneously at separate points in time, and (2) *continuous*,

* Portions of this chapter are based on Banks CM. What is modeling and simulation? In *Principles of Modeling and Simulation: A Multidisciplinary Approach*. Sokolowski JA, Banks CM (Eds.). Hoboken, NJ: John Wiley & Sons; 2009; VMASC short course notes prepared by Mikel D. Petty; and course notes prepared by Roland R. Mielke, Old Dominion University.

** Additional information and definitions of system can be found at the INCOSE online glossary at http://www.incose.org/mediarelations/glossaryofseterms.aspx.

where the state variables change continuously with respect to time. There are a number of ways to study a system:

(1) the actual system versus a model of the system
(2) a physical versus mathematical representation
(3) analytic solution versus simulation solution (which exercises the simulation for inputs to observe how they affect the output measures of performance) [1].

In the study of systems, the modeler focuses on three primary concerns: (1) the quantitative analysis of the systems; (2) the techniques for system design, control, or use; and (3) the measurement or evaluation of the system performance.

The second concept, *model*, is a physical, mathematical, or otherwise logical representation of a system, entity, phenomenon, or process. Simply, models serve as representations of events and/or things that are real (such as a historic case study) or contrived (a use case). They can be representations of actual systems. This is because systems can be difficult or impossible to investigate.

As introduced above, a system might be large and complex, or it might be dangerous to impose conditions for which to study the system. Systems that are expensive or essential cannot be taken out of service; systems that are notional do not have the physical components to conduct experiments. Thus, models are developed to serve as a stand-in for systems. As a substitute, the model is what will be investigated with the goal of learning more about the system.

To produce a model, one abstracts from reality a description of the system. However, it is important to note that a model is not meant to represent all aspects of the system being studied. That would be too timely, expensive, and complex—perhaps impossible. Instead, the model should be developed as simply as possible, representing only the system aspects that affect system performance being investigated in the model. Thus, the model can depict the system at some point of abstraction or at multiple levels of the abstraction with the goal of representing the system in a reliable fashion. Often, it is challenging for the modeler to decide which aspects of a system need to be included in the model.

A model can be *physical*, such as a scale model of an airplane to study aerodynamic behavior. A physical model, such as the scale model of an airplane, can be used to study the aerodynamic behavior of the airplane through wind-tunnel tests. At times, a model consists of a set of mathematical equations or logic statements that describes the behavior of the system. These are *notional* models. Simple equations often result in analytic solutions or an analytic representation of the desired system performance characteristic under study.

Conversely, in many cases, the mathematical model is sufficiently complex that the only way to solve the equations is numerically. This process is referred

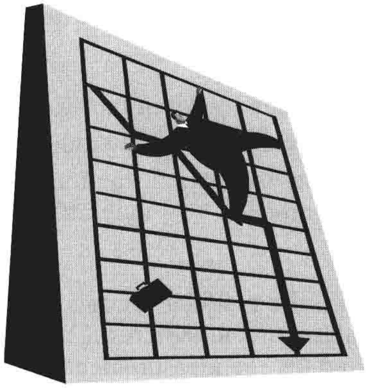

Figure 1.1 Model example.

to as *computer simulation*. Essentially, a system is modeled using mathematical equations; then, these equations are solved numerically using a digital computer to indicate likely system behavior. There are distinct differences between the numerical and the analytic way of solving a problem: Analytic solutions are precise mathematical proofs, and as such, they cannot be conducted for all classes of models. The alternative is to solve numerically with the understanding that an amount of error may be present in the numerical solution.

Below is an example of developing a model from a mathematical equation. The goal of the model is to represent the vertical height of an object moving in one dimension under the influence of gravity (Fig. 1.1).

The model takes the form of an equation relating the object height h to the time in motion t, the object initial height s, and the object initial velocity v, or:

$$h = \tfrac{1}{2}at^2 + vt + s,$$

where

h = height (feet),
t = time in motion (seconds),
v = initial velocity (feet per second, + is up),
s = initial height (feet),
a = acceleration (feet per second per second).

This model represents a first-order approximation to the height of the object. Conversely, the model fails, however, to represent the mass of the object, the effects of air resistance, and the location of the object.

Defining the third concept, *simulation*, is not as clear-cut as defining the model. Definitions of simulation vary:

(1) a method for implementing a model over time
(2) a technique for testing, analysis, or training in which real-world systems are used, or where real-world and conceptual systems are reproduced by a model
(3) an unobtrusive scientific method of inquiry involving experiments with a model, rather than with the portion of reality that the model represents
(4) a methodology for extracting information from a model by observing the behavior of the model as it is executed
(5) a nontechnical term meaning not real, imitation

In sum, simulation is an applied methodology that can describe the behavior of that system using either a mathematical model or a symbolic model [2]. It can be the imitation of the operation of a real-world process or system over a period of time [3].

Recall, engaging a real system is not always possible because (1) it might not be accessible, (2) it might be dangerous to engage the system, (3) it might be unacceptable to engage the system, or (4) the system might simply not exist. To counter these constraints, a computer will *imitate* operations of these various real-world facilities or processes. Thus, a simulation may be used when the real system cannot be engaged.

Simulation, simulation model, or software model is also used to refer to the software implementation of a model. The mathematical model of the Model Example 1 introduced above may be represented in a software model. The example below is a *C program* that calculates the height of an object moving under gravity:

Simulation Example 1

```
/* Height of an object moving under gravity. */
/* Initial height v and velocity s constants. */
main()
{
   float h, v = 100.0, s = 1000.0;
   int t;
   for (t = 0, h = s; h >= 0.0; t++)
   {
      h = (-16.0 * t * t) + (v * t) + s;
      printf("Height at time %d = %f\n", t, h);
   }
}
```

This is a software implementation of the model. In an actual application, *s* and *v* would be identified as input variables rather than constants. The result of simulating this model, executing the software program on a computer, is a series of values for *h* at specified times *t*.