MODELING AND SIMULATION FUNDAMENTALS

Theoretical Underpinnings and Practical Domains

Edited by

John A. Sokolowski
Catherine M. Banks

The Virginia Modeling Analysis and Simulation Center
Old Dominion University
Suffolk, VA

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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

CONTENTS

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.

John A. Sokolowski
Catherine M. Banks

CONTRIBUTORS

Catherine M. Banks, PhD, Virginia Modeling, Analysis, and Simulation Center, Old Dominion University, 1030 University Boulevard, Suffolk, VA 23435; Email: cmbanks@odu.edu

Joshua G. Behr, PhD, Department of Political Science and Geography, Old Dominion University, 5115 Hampton Boulevard, Norfolk, VA 23529; Email: jbehr@odu.edu

Wesley N. Colley, PhD, Senior Research Scientist, Center for Modeling, Simulation, and Analysis, University of Alabama, 301 Sparkman Drive, VBRH D-15, Huntsville, AL 35899; Email: colleyw@uah.edu

Rafael Diaz, PhD, Virginia Modeling, Analysis, and Simulation Center, Old Dominion University, 1030 University Boulevard, Suffolk, VA 23435; Email: rdiaz@odu.edu

Poornima Madhavan, PhD, Department of Psychology, Old Dominion University, 5115 Hampton Boulevard, Norfolk, VA 23529; Email: pmadhava@odu.edu

Frederic D. McKenzie, PhD, Department of Electrical and Computer Engineering, Old Dominion University, 5115 Hampton Boulevard, Norfolk, VA 23529; Email: rdmckenz@odu.edu

Roland R. Mielke, PhD, Department of Electrical and Computer Engineering, Old Dominion University, 5115 Hampton Boulevard, Norfolk, VA 23529; Email: rmielke@odu.edu

Yiannis Papelis, PhD, Virginia Modeling, Analysis, and Simulation Center, Old Dominion University, 1030 University Boulevard, Suffolk, VA 23435; Email: ypapelis@odu.edu

Mikel D. Petty, PhD, Director, Center for Modeling, Simulation, and Analysis, University of Alabama, 301 Sparkman Drive, VBRH D-14, Huntsville, AL 35899; Email: pettym@email.uah.edu

Yuzhong Shen, PhD, Department of Electrical and Computer Engineering, Old Dominion University, 5115 Hampton Boulevard, Norfolk, VA 23529; Email: yshen@odu.edu

Barry G. Silverman, PhD, Department of Systems Engineering, University of Pennsylvania, Philadelphia, PA 19104; Email: barryg@seas.upenn.edu

John A. Sokolowski, PhD, Virginia Modeling, Analysis, and Simulation Center, Old Dominion University, 1030 University Boulevard, Suffolk, VA 23435; Email: jsokolow@odu.edu

Andreas Tolk, PhD, Department of Engineering Management and Systems Engineering, Old Dominion University, 5115 Hampton Boulevard, Norfolk, VA 23529; Email: atolk@odu.edu

Gabriel A. Wainer, PhD, Department of Systems and Computer Engineering, Carleton University, 1125 Colonel By Drive, 3216 V-Sim, Ottawa, ON, K1S 5B6, Canada; Email: gwainer@sce.carleton.ca

Gnana K. Bharathy, Postdoctoral candidate, University of Pennsylvania, Philadelphia, PA 19104

G. Jiyun Kim, Postdoctoral candidate, University of Pennsylvania, Philadelphia, PA 19104

Mjumbe Poe, Research staff, University of Pennsylvania, Philadelphia, PA 19104

Mark Roddy, Research staff, University of Pennsylvania, Philadelphia, PA 19104

Khaldoon Al-Zoubi, Graduate Student, Carleton University, Ottawa, ON, K1S 5B6

Benjamin Nye, Graduate Student, University of Pennsylvania, Philadelphia, PA 19104

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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

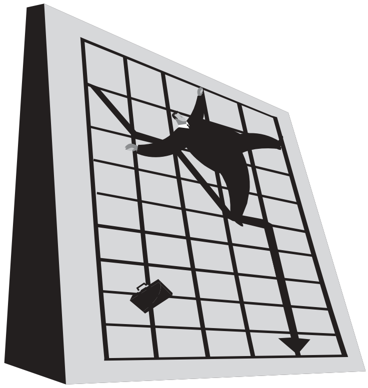

Figure 1.1 Model example.

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.

t	*v*	*h*
0	100	1000
1	68	1052
2	36	972
3	4	860
4	–28	719
5	–60	540
6	–92	332
7	–124	92

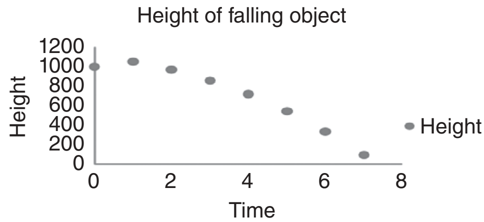

Figure 1.2 Tabular and graphic simulation.

Below is another output of the same model showing the results of simulating or executing the model of an object moving under the influence of gravity. The simulation is conducted for an initial height of $s = 1000$ ft, and an initial velocity of $v = 100$ ft/s. Note from the example that the positive reference for velocity is up, an acceleration of –32 ft/s/s. The results of the simulation are presented in tabular and graphic forms (Fig. 1.2):

Simulation Example 2

$$\text{Model:} \quad h = \tfrac{1}{2}at^2 + vt + sv = at + v_0$$

$$\text{Data:} \quad v_0 = 100\ \text{ft/s}, \quad s = 1000\ \text{ft}, \quad a = -32\ \text{ft/s}^2.$$

There are several terms associated with the execution of a simulation. The term *run* and/or *trial* is used to refer to a single execution of a simulation, as shown above. They may also refer to a series of related runs of a simulation as part of an analysis or experimentation process. The term *exercise* is used to refer to a series of related runs of the simulation as part of a training process. Thus, trial and exercise are similar in meaning but imply different uses of the simulation runs. Lastly, simulation also allows for virtual reality research whereby the analyst is immersed within the simulated world through the use of devices such as head-mounted display, data gloves, freedom sensors, and forced-feedback elements [2].

The fourth concept is *M&S*. M&S refers to the overall process of developing a model and then simulating that model to gather data concerning performance of a system. M&S uses models and simulations to develop data as a basis for making managerial, technical, and training decisions. For large, complex systems that have measures of uncertainty or variability, M&S might be the only feasible method of analysis of the system. M&S depends on computational science for the simulation of complex, large-scale phenomena. (Computational science is also needed to facilitate the fourth M&S precept, visualization, which serves to enhance the modeler's ability to understand or interpret that information. Visualization will be discussed in more detail below.)

In review, M&S begins with (1) developing computer simulation or a design based on a model of an actual or theoretical physical system, then (2) executing that model on a digital computer, and (3) analyzing the output. Models

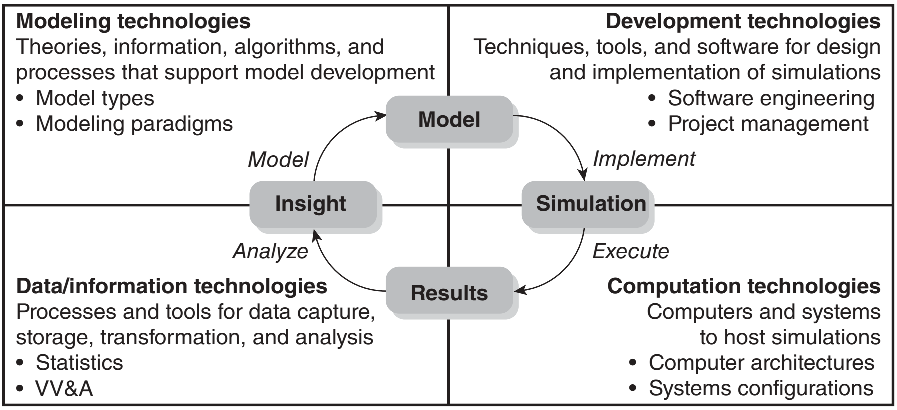

Figure 1.3 M&S cycle and relevant technologies (adapted from Starr and Orlov [4]).

and the ability to act out with models is a credible way of understanding the complexity and particulars of a real entity or system [2].

M&S Development Process Cycle

The process of M&S passes through four phases of a cyclic movement: model, code, execute, and analyze. Each phase depends on a different set of supporting technologies:

(1) model phase = modeling technologies
(2) code phase = development technologies
(3) execute phase = computational technologies
(4) analyze phase = data/information technologies

Figure 1.3 illustrates these phases and their related technologies [4]. The figure also depicts two processes: (1) the phases used in the development and testing of computer models and simulations and 2) the phases involved in applying M&S to the investigation of a real-world system.

Modeling Technologies The construction of a model for a system requires data, knowledge, and insight about the sysyem. Different types of systems are modeled using different constructs or paradigms. The modeler must be proficient in his or her understanding of these different system classes and select the best modeling paradigm to capture or represent the system he or she is to model. As noted previoulsy, modeling involves mathematics and logic to describe expected behavior; as such, only those system behaviors siginificant to the study or research question need be represented in the model.

Development Technologies The development of a simulation is a software design project. Computer code must be written to algorithmically represent the mathematical statements and logical constructs of the model. This phase of the M&S cycle uses principles and tools of software engineering.

Computational Technologies The simulation is next executed to produce performance data for the system. For simple simulations, this might mean implementing the simulation code on a personal computer. For complex simulations, the simulation code might be implemented in a distributed, multiprocessor or multicomputer environment where the different processing units are interconnected over a high-speed computer network. Such an implementation often requires specialized knowledge of computer architectures, computer networks, and distributed computing methodologies.

Data/Informational Technologies During this phase of the M&S process, analysis of the simulation output data is conducted to produce the desired performance information that was the original focus of the M&S study. If the model contains variability and uncertainty, then techniques from probability and statistics will likely be required for the analysis. If the focus of the study is to optimize performance, then appropriate optimization techniques must be applied to analyze the simulation results.

The desired M&S process will undoubtedly take a number of iterations of the M&S cycle. The first iteration often provides information for modifying the model. It is a good practice to repeat the cycle as often as needed until the simulation team is satisfied that the results from the M&S study are close enough to the performance of the system being studied.

Figure 1.4 provides a more detailed view of the M&S cycle with the addition of details such as verification, validation, and accreditation (VV&A) activities, which serve to ensure a more correct and representative model of the system [5]. (The *dashed connectors* show how the process advances from one phase to the next. The *solid connectors* show the VV&A activities that must be integrated with the development activities.)

Verification Verification ensures that M&S development is conducted correctly, while *validation* ensures that the model represents the real system and that the model is truly representative of that system. (Chapter 10 will provide a thorough discussion on the subject of VV&A.) This diagram illustrates how VV&A activities are not conducted as a phase of the M&S process, but as activities integrated throughout the M&S process.

To engage the entire M&S process, a number of related concepts and disciplines must be incorporated into the cycle.

Related Disciplines

There are five key concepts and/or disciplines related to the M&S process: probability and statistics, analysis and operations research, computer visualization, human factors, and project management. Each will be briefly discussed.

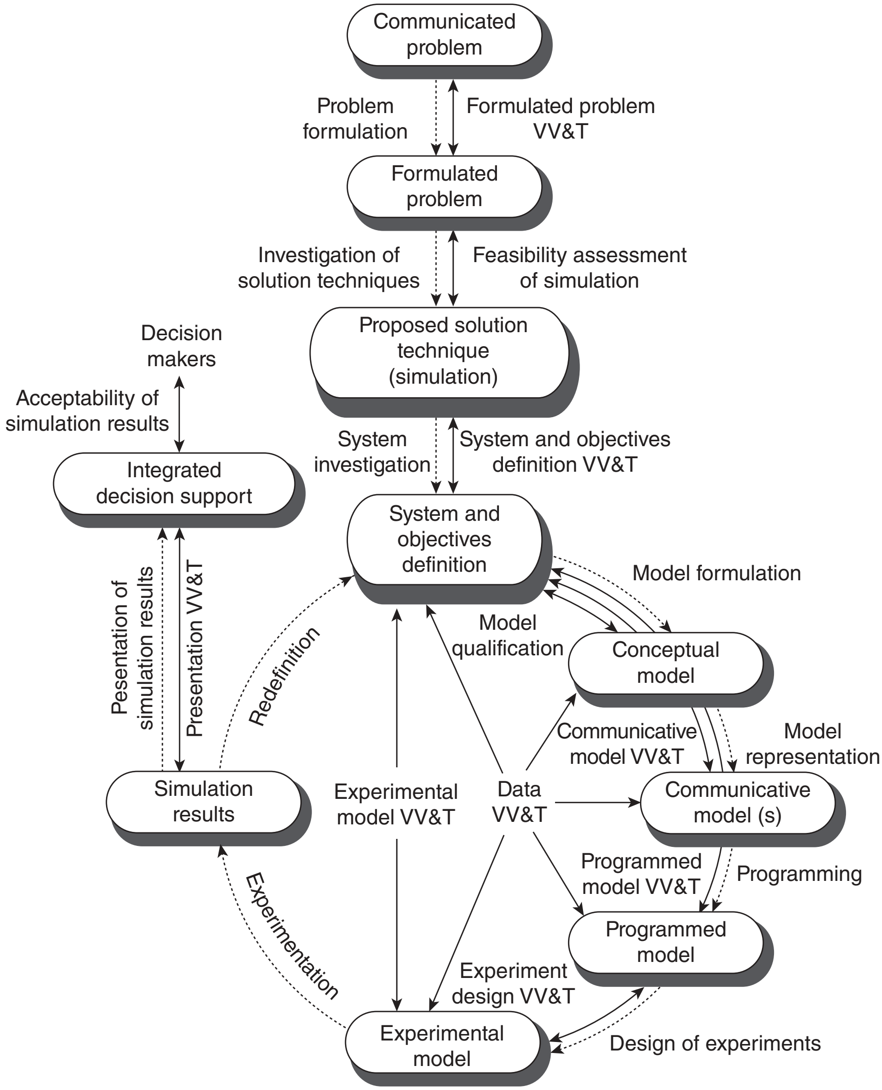

Figure 1.4 Detailed M&S life cycle (adapted from Balci [5]). VV&T, verification, validation, and testing.

Probability and Statistics Nearly all systems in the real-world display varying degrees of uncertainty. For instance, there is uncertainty in the movement of cars at a stop light:

(1) How long before the first car acknowledges the light change to green?
(2) How fast does that car take off?
(3) At what time does the second car start moving?

(4) What is the spatial interval between cars?
(5) What happens if one of the cars in the chain stalls?

In modeling a situation such as traffic movement at a stop light, one cannot ignore or attempt to average the uncertainty of response/movement because the model would then lack validity. Inclusion of uncertainty and variability requires that system parameters be represented as *random variables* or *random process*.

Working with random variables requires the use of concepts and theories from *probability and statistics*, a branch of mathematics. Probability and statistics are used with great frequency in M&S to generate random variates to model system random input variables that represent uncertainty and variability, and to anaylze the output from *stochastic models* or systems.

Stochastic models contain parameters that are described by random variables; thus, simulation of stochastic models results in outputs that are also random variables. Probability and statistics are key to analysis of these types of systems. Chapters 2 and 5 will provide further discussion of this significant branch of mathematics.

Analysis and Operations Research The conduct of a simulation study results in the generation of system performance data, most often in large quantities. These data are stored in a computer system as large arrays of numbers. The process of converting the data into meaningful information that describes the behavior of the system is called *analysis*. There are numerous techniques and approaches to conducting analysis. The development and use of these techniques and approaches are a function of the branch of mathematics and systems engineering called *operations research*.

M&S-based analysis has a simulation output that typically represents a dynamic response of the modeled system for a given set of conditions and inputs. Analysis is performed to transform these data when seeking answers to questions that motivated the simulation study. The simulation study can include a number of functions:

(1) *design of experiments*—the design of a set of simulation experiments suitable for addressing a specific system performance question;
(2) *performance evaluation*—the evaluation of system performance, measurement of how it approaches a desired performance level;
(3) *sensitivity analysis*—system sensitivity to a set of input parameters;
(4) *system comparison*—comparison of two or more system alternatives to derive best system performance with given conditions;
(5) *constrained optimization*—determination of optimum parameters to derive system performance objective.

Recall, analysis is one of the four precepts of M&S (along with modeling, simulation, and visualization). Simply, analysis takes place to draw conclusions, verify and validate the research, and make recommendations based on various simulations of the model. Chapter 4 delves further on the topics of queuing theory-based models, simulation methodology, and spreadsheet simulation—all functions of analysis.

Computer Visualization Visualization is the ability to represent data as a way to interface with the model. (It is also one of the four precepts of M&S.) The systems that are investigated using M&S are large and complex; too often tables of data and graphs are cumbersome and do not serve to clearly understand the behavior of systems. Visualization is used to represent the data.

Computer graphics and computer visualization are used to construct two-dimensional and three-dimensional models of the system being modeled. This allows for the visual plotting and display of *system time response functions* to visualize complex data sets and to animate visual representations of systems to understand its dynamic behavior more adequately. M&S professionals who are able to engage *visualization* fully are able to provide an overview of interactive, real-time, three-dimensional computer graphics and visual simulations using high-level development tools. These tools facilitate virtual reality research, whereby the analyst is immersed within the simulated world through the use of devices such as head-mounted display, data gloves, freedom sensors, and forced-feedback elements [2]. *Computer animations* are offshoots of computational science that allow for additional variations in modeling.* Chapter 7 will provide an in-depth discussion of visualization.

Human Factors Most simulations are developed to interface with a human user. These simulations place humans as system components within the model. To do this efficiently and effectively, the simulation designer must have a basic understanding of human cognition and perception. With this knowledge, the simulation designer can then create the human–computer interface to account for the strengths and weaknesses of the human user. These areas of study are called *human factors* and *human–computer interfacing*. The modeling of human factors is called *human behavior modeling*. This type of modeling focuses primarily on the computational process of human decision making. All three areas of study are typically subareas of psychology, although disciplines within the social sciences (such as history, geography, religious studies, political science) also make significant contributions to human behavior modeling.** Chapter 9 addresses human factors in M&S.

Project Management The application of the M&S process to solve real-world problems is a daunting task, and, if not managed properly, it can become

* *Computer animation* is emphasized within computer graphics, and it allows the modeler to create a more cohesive model by basing the animation on more complex model types. With the increased use of system modeling, there has been an increased use of computer animation, also called physically based modeling [4].

** For more information on human behavior modeling and case studies using systems dynamics, game theory, social network modeling, and ABM to represent human behavior, see Sokolowski JA, Banks CM. (Eds.). *Principles of Modeling and Simulation: A Multidisciplinary Approach*. New York: John Wiley & Sons; 2009; and Sokolowski JA, Banks CM. *Modeling and Simulation for Analyzing Global Events*. New York: John Wiley & Sons; 2009.

a problem in itself. For instance, there might be thousands of people and months of effort invested in a project requiring effective and efficient management tools to facilitate smooth outlay. When computer simulation is the only method available to investigate such large-scale projects, the M&S process becomes a large technical project requiring oversight and management. Thus, the M&S professional must be acquainted with project management, a subarea of engineering management.

With this introduction of M&S fundamentals, what is meant by M&S and the related areas of study that are important to the M&S process, one can progress to a more detailed discussion of M&S characteristics, paradigms, attributes, and applications.

M&S CHARACTERISTICS AND DESCRIPTORS

Understanding what is meant by M&S and how, as a process, it can serve a broad venue of research and development is one's initial entry into the M&S community. As M&S professionals, one must progress to understanding and engaging various simulation paradigms and modeling methods. The information below will introduce some of these characteristics and descriptors.

Simulation Paradigms

There are different simulation paradigms that are prominent in the M&S process. First, there is the *Monte Carlo simulation* (also called the Monte Carlo method), which randomly samples values from each input variable distribution and uses that sample to calculate the model's output. This process of random sampling is repeated until there is a sense of how the output varies given the random input values. Monte Carlo simulation models system behavior using probabilities. Second is *continuous simulation* whereby the system variables are *continuous functions of time*. Time is the independent variable and the system variables evolve as time progresses. Continuous simulations systems make use of differential equations in developing the model. The third simulation paradigm is *discrete-event simulation* in which the system variables are *discrete functions in time*. These discrete functions in time result in system variables that change only at distinct instants of time. The changes are associated with an occurence of a system event. Discrete-event simulations advance time from one event to the next event. This simulation paradigm adheres to queuing theory models. Continuous and discrete-event simulations are *dynamic systems* with variables changing over time. All three of these simulation paradigms are discussed individually in Chapters 2–4.

M&S Attributes

There are three primary descriptors applied to a *model* or *simulation* that serve as attributes or defining properties/characteristics of the model or simulation. These are fidelity, resolution, and scale.

Fidelity is a term used to describe how the model or the simulation closely matches reality. The model or simulation that closely matches or behaves like the real system it is representing has a high fidelity. Attaining high fidelity is not easy because models can never capture every aspect of a system. Models are built to characterize only the aspects of a system that are to be investigated. A great degree of effort is made to achieve high fidelity. A low fidelity is tolerated with regard to the components of the system that are not important to the invesigation. Similarly, different applications might call for different levels of fidelity. The simulation of the system for thesis research and development may require higher levels of fidelity than a model that is to be used for training.

Often, the term fidelity is used incorrectly with *validity* to express the accuracy of the representation. Only validity conveys three constructs of accuracy of the model:

(1) *reality*—how the model closely matches reality
(2) *representation*—some aspects are represented, some are not
(3) *requirements*—different levels of fidelity required for different applications.

Resolution (also known as granularity) is the degree of detail with which the real world is simulated. The more detail included in the simulation, the higher the resolution. A simple illustration would be the simulation of an orange tree. A simulation that represents an entire grove would prove to have a much lower resolution of the trees than a simulation of a single tree. Simulations can go from low to high resolution. Return to the example of the tree: The model can begin with a representation of the entire forest, then a model of an individual tree, then a model of that individual tree's fruit, with a separate model of each piece of fruit in varying stages of maturity.

Scale is the size of the overall scenario or event the simulation represents; this is also known as level. Logically, the larger the system or scenario, the larger the scale of the simulation. Take for example a clothing factory. The simulation of a single sewing machine on the factory floor would consist of a few simulation components, and it would require the representation of only a few square feet of the entire factory. Conversely, a simulation of the entire factory would require representations of all machines, perhaps hundreds of simulation components, spread out over several hundred thousand square feet of factory space. Obviously, the simulation of the single sewing machine would have a much smaller scale than the simulation of the entire factory.

With an understanding of fidelity, resolution, and scale as individual attributes of M&S comes the ability to join these attributes to one another. The ability to relate fidelity and resolution, or fidelity and scale, or resolution and scale provides insight to the different types of simulations being used today. Table 1.1 is a comparison of *fidelity and resolution* premised on the common

Table 1.1 Comparing fidelity and resolution

	Fidelity	
Resolution	Low	High
Low	Board game—*chess*	Agent-based simulation—*Swarm*
High	Personal computer flight simulator—*Microsoft Flight Simulator*	Platform-level training simulation—airline flight simulator

Table 1.2 Comparing fidelity and scale

	Fidelity	
Scale	Low	High
High	Board game—*Battleground*	Massive multiplayer online games—*World of Warcraft*
Low	Personal computer combat simulator—*Doom*	First-person shooter—*Halo*

assumption that increasing resolution increases fidelity. This premise is not absolute because it is possible to increase the resolution of the simulation without increasing the fidelity of the simulation. Note the four combinations of fidelity–resolution.

The assumption held regarding *fidelity and scale* is that increasing scale results in decreasing fidelity. This assumption is unsound. As scale increases, it is likely that there will be an increase in the number of simulated entities. However, what if there is an aggregation of closely related entities as a single simulation entity? If the research question of the system sought to address behavior of related groups, then the increasing scale might have no effect on the fidelity of the simulation. Note the four combinations of fidelity–scale in Table 1.2.

The final comparison is that of *resolution and scale*. In general terms, more resolution leads to less scale and vice versa. Increasing scale results in decreasing resolution. This is due to the fact that the computing system hosting the simulation has a finite limit on the computing capability, especially since each simulation entity requires a specific amount of computational power for a given level of resolution. As scale increases, the number of entities increases, and these entities require additional computational capability. If the computational capability is at its limit, then increases in scale can only take place if the resolution of the simulation is lowered. As a result, high resolution, high-scale simulations are constrained by computing requirements. Note the four combinations of resolution–scale in Table 1.3.

Once a model has been developed with the correct simulation paradigm engaged and a full appreciation of fidelity, resolution, and scale as attributes