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INTRODUCTION TO MODELING AND SIMULATION

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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

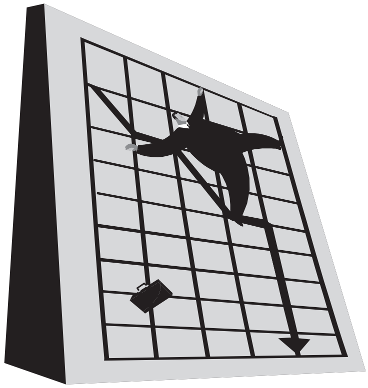

Figure 1.1 Model example.

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

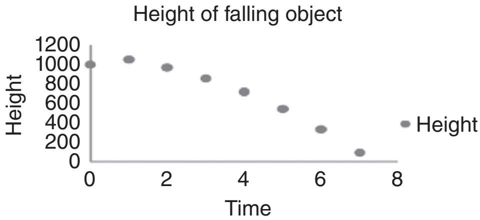

Figure 1.2 Tabular and graphic simulation.

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

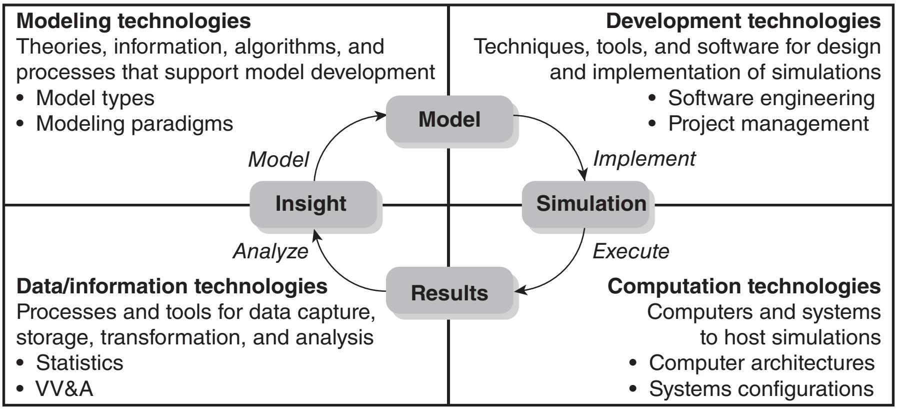

Figure 1.3 M&S cycle and relevant technologies (adapted from Starr and Orlov [4]).

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.

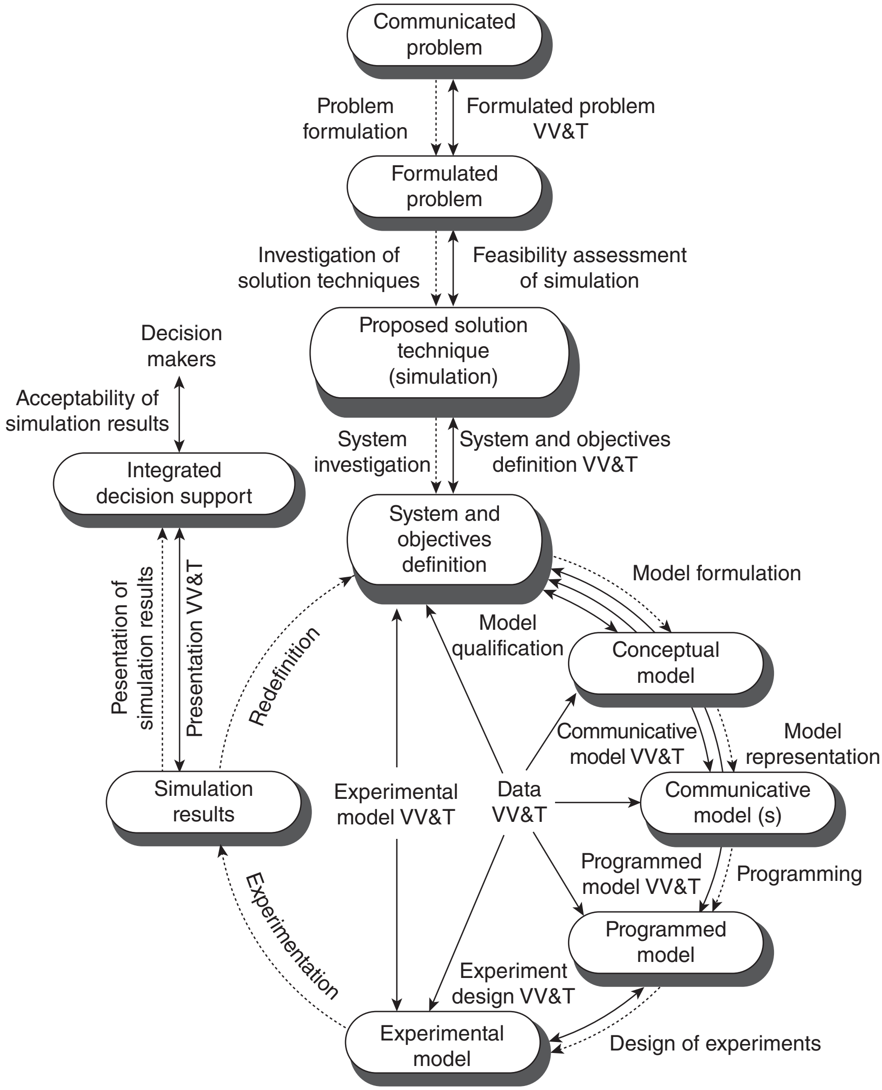

Figure 1.4 Detailed M&S life cycle (adapted from Balci [5]). VV&T, verification, validation, and testing.

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

Table 1.3 Comparing resolution and scale

	Scale	
Resolution	Low	High
Low	Not interesting	Operational-level training simulation—*WarSim*
High	Urban warfare personal computer game—*Shrapnel: Urban Warfare 2025*	Not practical

of the simulation acknowledged, the modeler must then consider, *is the model correct and usable*? This is done through the process of verification and validation (V&V).

VV&A Process

No discussion of M&S characteristics and descriptors would be complete without addressing the importance of the VV&A process. VV&A is the process of determining if the model and/or simulation is correct and usable for the purpose of which it has been designed. Simply, one might ask, was the model *built correctly* and was it the *correct model*? It is also the process of developing and delimiting confidence that a model can be used for a specific purpose. The first phase, *verification*, is the process of determining if a model accurately represents the conceptual description and specifications of the model. Verification requires a check on the coding by determining if the simulation is coded correctly. Asking, *does the simulation code correctly implement the model* is the way verification tests the software quality. A number of software engineering tests and techniques that are part of the verification process will be introduced in Chapter 10.

The process of determining the degree to which a model is an accurate representation of the real-world system from the perspective of the model's intended use is *validation*. Validity answers the question, *is the right thing coded* or *how well does the model match reality in the context of purpose of the model*? Validity speaks to modeling quality. In essence, validity is a measure of model fidelity in a specific application of the model. Validation methods or techniques exist to verify and validate a model and its simulation. These techniques go from *informal* to *inspection-like* to *formal* with the use of logic to prove correctness. Table 1.4 is a small representation of some of these techniques [5].

The third aspect of VV&A is the process of accreditation as the official certification by a responsible authority that a model is acceptable for a specific use [6]. The authority is an agency or person responsible for the results of using the model. As such, the authority should be separate from the developer of the model or simulation. This is not a general-purpose approval as each model is accredited for a specific purpose or use.

Table 1.4 Verification and validation techniques

Informal	Static	Dynamic	Formal
Audit	Cause–effect graphing	Acceptance testing	Induction
Desk checking	Control analysis	Alpha testing	Inductive assertions
Documentation checking	Data analysis	Assertion checking	Inference
Face validation	Fault/failure analysis	Beta testing	Logical deduction
Inspections	Interface analysis	Bottom-up testing	Lambda calculus
Reviews	Semantic analysis	Comparison testing	Predicate calculus
Turing test	Structural analysis	Statistical techniques	Predicate transformation
Walkthroughs	Symbolic analysis	Structural testing	Proof of correctness
	Syntax analysis	Submodel/ module testing	
	Traceability assessment	Visualization/ animation	

Model Types

The final subtopic under M&S characteristics and descriptors is *model types*. The following modeling types are common in M&S, and this listing will serve to define these modeling methods succinctly. Discussion of many of the model types will be developed in greater detail in the following chapters.

Physics-Based Modeling Physics-based modeling is solidly grounded in mathematics. A physics-based model is a mathematical model where the model equations are derived from basic physical principles. Model Example 1 is a physics-based model. Unique to physics-based models is the fact that the physics equations are models themselves in that many physics-based models are not truly things—they are intangibles; hence, they are representations of phenomena. Another example is Newton's law of gravity, which describes the gravitational attraction between bodies with mass. His idea was first published in 1687; in contemporary text it reads:

Every point mass attracts every other point mass by a force pointing along the line intersecting both points. The force is directly proportional to the product of the two masses and inversely proportional to the square of the distance between the point masses:

$$F = G\frac{m_1 m_2}{r^2},$$

where

F is the magnitude of the gravitational force between the two point masses
G is the gravitational constant
m_1 is the mass of the first point mass
m_2 is the mass of the second point mass
r is the distance between the two point masses.

Physics-based models are based on *first principles* (as such, they may be referred to as first principle models). These principles, however, do not guarantee fidelity as this type of model may not represent all aspects of a system, or it might be based on assumptions that constrain the use of the model so that it is suitable only under certain conditions. There may be assumptions and omissions that affect the fidelity. Going back to Model Example 1, the height of the building is recognized but not the air resistance—and the model assumes the location will be near the surface of the Earth.

Physics-based models may also suffer *invalid composition*. This occurs when many simulations combine multiple physics-based models. Combining multiple models usually takes place with the development of a large-scale model; in essence, larger-scale models are the combination of smaller-scale models. When this combination takes place, changes to one or many of the models' components result. When this occurs, there might be invalid composition.

Finite Element Modeling (FEM) FEM is the method used for modeling large or complicated objects by decomposing these elements into a set of small elements and then modeling the small elements. This type of modeling is widely used for engineering simulation, particularly mechanical and aerospace engineering. These subdisciplines conduct research that requires structural analysis or fluid dynamics problems. FEM facilitates the decomposition of a large object into a set of smaller objects labeled *elements*.

These individual elements and the neighbor relationships that occur with elements in proximity are represented by a mesh of nodes. The state of the nodes is modeled using physics-based equations that take into account the current state of the node, the previous state, the state of the nearest neighboring node, and any knowledge of interactions between the neighbors. These computations of the state of the nodes are iterated over simulation time.

Data-Based Modeling Data-based modeling results from models based on data describing represented aspects of the subject of the model. Model development begins with advanced research or data collection, which is used in simulations. Data sources for this type of modeling can include actual field experience via the real-world or real system, operational testing and evaluation of a real system, other simulations of the system, and qualitative and quantitative research, as well as best guesses from subject matter experts. The model is developed with the view that the system is exercised under varying conditions with varying inputs. As the outputs unfold, their results are recorded and tabulated so as to review appropriate responses whenever similar conditions and inputs are present in the model.

Data-based modeling is often used when the real system cannot be engaged or when the subject of the model is notional. When the physics of the model subject is not understood or computations costs are high, data-based modeling can substitute. This modeling relies on data availability—it functions at its best when the data are accurate and reliable.

Agent-Based Modeling (ABM) ABM is an important modeling paradigm for investigating many types of human and social phenomena [7]. The important idea here is that of a computer being able to create a complex system on its own by following a set of rules or directions and not having the complex system defined beforehand by a human. ABMs consist of *agents* that are defined as *autonomous software entities that interact with their environment or other agents to achieve some goal or accomplish some task*. This definition has several important elements to recognize. Probably the most important of these elements is the concept of *autonomy*. This characteristic is what sets agents apart from other object-oriented constructs in computer science. Agents act in their own self-interest independent of the control of other agents in the system. That is not to say that they are not influenced by other agents. They do not take direction from other agents. Because of this autonomy, each agent decides for itself what it will do, when it will do it, and how it will be done. These decisions are based on behaviors incorporated into the agent by its designer.

An agent's *environment* and the existence of other agents in that environment also play a key role on how an agent may behave. An agent is embodied with the ability to sense its environment, which includes everything it is aware of external to itself except other agents. As it senses this environment, it may respond to changes in it or it may just observe the changes waiting for a specific event to take place. It is also aware of the other agents. It may monitor what they are doing and may communicate with them to request they accomplish some task or it may respond to a request it has received. This closely represents how a human interacts with its surroundings and the other persons in it.

Finally, an agent acts to achieve some *goal* or accomplish some task. A task may be to retrieve a piece of data from a specific source or move to a certain location in virtual space. Task accomplishment is generally reactive in nature and does not require some complex set of reasoning to carry out. The use of artificial intelligence techniques can be incorporated into the model to modify the behavior of agents and rules of interaction among them. As such, ABMs vary widely in implementation and level of sophistication. (For a detailed discussion, see Sokolowski and Banks [8].)

Aggregate Modeling This modeling method facilitates a number of smaller objects and actions represented in a combined, or aggregated, manner. Aggregate models are used most commonly when the focus of the M&S study is on aggregate performance. The model can also scale and number represented entities that are large and can compromise the time required to conduct a simulation. These models are most often used in constructive models; they are not physics-based models.

Hybrid Modeling Hybrid modeling entails combining more than one modeling paradigm. This type of modeling is becoming a common practice among model developers. Hybrid modeling makes use of several modeling methods; however, they are disadvantaged in that composing several different types of models correctly is a difficult process.

There are numerous other model types. Some of these include Markov chains, finite-state automata, particle systems, queuing models, bond graphs, and Petri nets. The challenge for the modeler is to choose the best modeling paradigm that represents the designated system and answer specific research questions or training needs.

M&S CATEGORIES

Categorizing models and simulations into different groupings or assemblages is a useful exercise in that it facilitates a clearer understanding of what makes some models and simulations similar and some different. This grouping or partitioning of models and simulations is grounded on shared, common characteristics. Categorizing models and simulations establishes what can be considered *coordinates of M&S space*. Where a model or simulation is placed in this space identifies its individual properties. There are four category dimensions: type, application, randomness, and domain.

Type

M&S is classed into three types: live, virtual, and constructive. These types vary in operator and environment. For example, the model and simulation can include real people doing real things, or real people operating in unreal or simulated environments, and real people making inputs into simulations that execute those inputs by simulated people.

A *live simulation* involves real people operating real systems. This simulation strives to be as close as possible to real use, and it often involves real equipment or systems. The military train using live simulation when they conduct war games that place real soldiers and real platforms in an engagement situation in which actual weapon firings or impacts have been replaced with instrumentation. The purpose of live simulation training is to provide a meaningful and useful experience for the trainee.

A *virtual simulation* is different from live simulation in that it involves real people operating in simulated systems. These systems are recreated with

Table 1.5 M&S types

Category	Participants	Systems
Live	Real	Real
Virtual	Real	Simulated
Constructive	Simulated	Simulated

simulators, and they are designed to immerse the user in a realistic environment. A good example of virtual simulation training is the cockpit simulator used to train aircraft pilots. This simulator uses a physical representation of the actual cockpit with computer models to generate flight dynamics, out-of-window visuals, and various environmental/atmospheric changes to which the pilot must respond. This type of training is designed to provide useful piloting experience without leaving the ground.

The third type of M&S is *constructive simulation*. This simulation involves real people making inputs into a simulation that carry out those inputs by simulated people operating in simulated systems. As real people provide directives or inputs, activity begins within the simulation. There are no virtual environments or simulators, and the systems are operated by nonparticipants. The expected result of constructive simulation is that it will provide a useful result. The military has made use of constructive simulation via the modular semiautomated forces (ModSAF). ModSAF is a constructive combat model designed to train doctrine and rules of engagement. Table 1.5 delineates the types of simulation and the nature of the participants and systems.

In sum, the three categories are distingushed by the nature of the participants and the systems. One of the challenges for modelers, in both engineering and sciences, is to combine the live, virtual, and constructive simulations into a single training environment. That environment is well constructed when the participants are unable to indentify if they are contending with real, virtual, or constructive threats.

Applications

The purposes for developing models and simulations vary. These purposes, also called *applications*, include training, analysis, experimentation, engineering, and acquisition. As discussed above, training is key to model development and simulation categorization. Relative to applications, the intent of *training* is to produce learning in the user (or participant). The training environment or the training activity must be realistic to the point that it produces effective, useful skills and/or knowledge. Training in a simulated environment or a simulation is safe, reliable, and less costly. Because this environment is reproducible, it can outlast a live-training environment. One drawback to training is that it can also produce negative learning or habits. Care must be taken so that the experiences in which the participant is learning are present in the real environment, and any scenarios or situations in which the learned responses are not present in the real environment should be removed.

Analysis as an application is the process of conducting a detailed study of a system to prepare for the design, testing, performance, evaluation, and/or prediction of behavior in different environments. The system can be real or notional. Simulation is often used for analysis; however, these simulations require a higher degree of fidelity than would simulations developed for training. There must also be a carefully crafted experimental design in that trials planned in advance will cover many cases and a sufficient number of trials are conducted to achieve statistical significance.

A third application or purpose for using M&S is *experimentation*. The intent of experimentation is used to explore design or solution spaces; it also serves to gain insight into an incompletely understood situation [9]. Experimentaion is likened to analysis; however, it lacks some of the structure and control found in analysis. Simply, experimentation allows for the *what-if* questions; it explores possibilities and varying outcomes. Experimentation is an iterative process of collecting, developing, and exploring concepts to identify and recommend value-added solutions for change.

In conjunction with M&S, *engineering applications* are used to design systems. These designs can be tested or changed in the simulation. Validity is the desired end with an engineering application. Engineering applications begin at the undergraduate level where students are taught the development of a model and ways to execute—simulate—the model. Simulation tools used in this application include finite element M&S tools, MATLAB (for modeling continuous systems), and ARENA (for modeling discrete-event systems).

The *acquisition application* entails the process of specifying, designing, developing, and implementing new systems. The process includes the entire life cycle of a system from concept to disposal. The intent of this application is to use the simulation to evaluate cost-effectiveness and correctness before committing funds for an acquisition.

Randomness

The concept of randomness is simple: Does an M&S process include uncertainty and variability? Randomness is comprised of two types of simulations: deterministic and stochastic. *Deterministic simulation* takes place when a given set of inputs produce a determined, unique set of outputs. Thus, these simulations include *no* uncertainty and *no* variability. Physics-based simulations and engineering simulations can be deterministic simulations. For both deterministic and stochastic simulations, output is determined by input. Conversely, *stochastic simulation* accepts random variables as inputs, which logically lead to random outputs. This type of simulation is more difficult to represent and analyze because appropriate statistical techniques must be used. Thus, these simulations *do* include uncertainty and variability. Stochastic simulations are common in models for discrete-event systems.

Domains

The *domain* of an M&S process refers to the subject area of the process. There are numerous domains, and as M&S becomes fluent in the user community, more domains will be engaged. Of course, the military has been using M&S for many years and so military simulation as a domain has a long association with research, development, and the education components of M&S. Within the past decade, a number of other domains have made inroads in the M&S community: transportation, decision support, training and education (aka game-based learning), medical simulation, homeland security simulation, M&S for the social sciences, and virtual environments.

M&S as a discipline is expanding the body of knowledge in an effort to explain the theory and ontology of M&S. This will no doubt spawn professionals who will develop models that can faciliate investigation in the various domains. As research and development continue, the user community (non-M&S academics or professionals) will be able to make use of M&S as a tool for representing their findings, predicting outcomes, and proffering solutions.

CONCLUSION

This chapter introduced three fundamental precepts of M&S: the basic notion that *models* are approximations for the real world; a well-developed model can then be followed by *simulation*, which allows for the repeated observation of the model; and that *analysis* facilitates drawing conclusions, V&V, and recommendations based on various iterations/simulations of the model. These three principles coupled with *visualization*, the ability to represent data as a way to interface with the model, make M&S a problem-based discipline that allows for repeated testing of a hypothesis.

Those who chose to engage M&S are aware of its useful attributes:

(1) It allows for precise abstraction of reality.
(2) It hosts a methodology to master complexity.
(3) It requires techniques and tools.
(4) It is validated by solid mathematical foundations.

These attributes lend themselves to better research and analyses. Note the advantages to using M&S as determined by the Institute of Industrial Engineers (IIE) [10]. In 1998, IIE published the following list:

(1) The ability to *choose correctly* by testing every aspect of a proposed change without committing additional resources
(2) *Compress and expand time* to allow the user to speed up or slow down behavior or phenomena to facilitate in-depth research

(3) *Understand why* by reconstructing the scenario and examining the scenario closely by controlling the system
(4) *Explore possibilities* in the context of policies, operating procedures, and methods without disrupting the actual or real system
(5) *Diagnose problems* by understanding the interaction among variables that make up complex systems
(6) *Identify constraints* by reviewing delays on process, information, and materials to ascertain whether or not the constraint is the effect or cause
(7) *Develop understanding* by observing how a system operates rather than predictions about how it will operate
(8) *Visualize the plan* with the use of animation to observe the system or organization actually operating
(9) *Build consensus* for an objective opinion because M&S can avoid inferences
(10) *Prepare for change* by answering the "what if" in the design or modification of the system
(11) *Invest wisely* because a simulated study costs much less than the cost of changing or modifying a system
(12) *Better training* can be done less expensively and with less disruption than on-the-job training
(13) *Specify requirements* for a system design that can be modified to reach the desired goal.*

The chapter also introduced related disciplines and concepts such as probability and statistics, analysis and operations research, computer visualization, human factors, and project management—all integral to the M&S process. The discussion on modeling paradigms and types introduced three simulations: Monte Carlo, continuous, and discrete event. A review of attributes, fidelity, resolution, and scale, as well as their distribution emphasized the importance of understanding the intent of the model so that the modeler can give attention to the appropriate attribute. The importance of V&V in model creation must be stressed for any model (and modeler) to retain credibility.

Understanding the various model types, physics-based, finite element, data-based, agent-based, and so on, is important for all students of M&S. Whether the simulation is live, virtual, or constructive; whether it is used for training, analysis, experimentation, acquisition, or engineering; and whether

*The IIE also made a noticeably shorter list of the disadvantages: *special training* needed for building models; *difficulty in interpreting results* when the observation may be the result of system interrelationships or randomness; *cost in money and time* due to the fact that simulation modeling and analysis can be time consuming and expensive; and *inappropriate use* of M&S when an analytic solution is best.

is it deterministic or stochastic, the M&S professional must understand all of these concepts and capabilities and how they come into play in model development. Lastly, the chapter listed some of the domains in which M&S is leading in research and development: military, homeland security, medical, transportation, education and training, decision support, M&S for the social sciences, and virtual environments.

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