2 Modeling and Simulation Method

2.1 INTRODUCTION

Modeling and simulation (M&S) projects vary widely according to the nature of what is represented, the simulation paradigm employed, the modeling purpose, and the size of the modeling effort. Therefore, modeling processes and methodologies employed can be very different across projects. For example, a continuous model of traffic patterns might be constructed within a few days by a single modeler to illustrate the effects of a road maintenance project over a two-year period. On the other hand, a large discrete event model for managing automobile manufacturing supply chains might be developed and maintained by a large modeling team.

Simulation is used to represent the behavior of systems, processes, or scenarios. A system view is concerned with inputs to a system boundary, their transformation, and outputs across the system boundary. A process view is concerned with a series of steps, each step having inputs, performing a transformation, and producing an output. Scenarios in the context of training or gaming describe an environment with situational factors and actions performed. This book is primarily concerned with modeling and simulating real systems and processes, though it is not meant to exclude scenarios. In this book, a reality represented in a model may be referred to as a system, a system or process, a subject target, or a subject.

Understanding behavior is the usual reason for M&S. Even a simple process can have complex behavior, but simulation models often become complex because they represent systems or processes composed of many elements having many relationships and the overall behaviors are complex. Real complexity can complicate the modeling unnecessarily unless a disciplined approach is used.

The basis for a disciplined approach is the sequence of modeling stages discussed in this chapter with the caveat that modeling is not a strictly sequential process of engagement, specification, construction, verification and validation, experimentation, and reporting shown in Figure 2.1. Rather, a modeler undertakes these stages iteratively. For example, during engagement, a modeler may realize that a particular part of a system would be most difficult to represent, and so may specify that part at a high level of abstraction for discussion with the sponsor. The modeler may even construct a small model to take back to the sponsor for elucidation of the system workings and validation of modeling scope. Elaboration of the model would proceed with further iterations that respect the sequence of the stages.

Despite the wide variety of modeling projects, a general method for modeling and simulation can be described. As it is described, the need for specialized knowledge and skills will become apparent, therefore these are discussed later in this chapter.

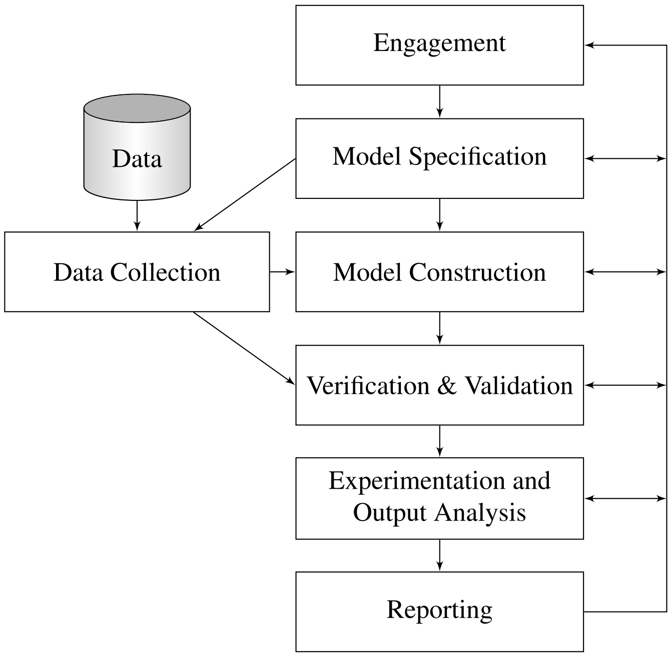

FIGURE 2.1: Modeling Process

2.2 ENGAGEMENT

When engaging with a customer for a modeling project, the customer may not have been exposed to M&S studies and so may not know how an M&S study can help. In this case, the modeler must spend time with the customer discussing what problems the customer perceives, why the customer thinks an M&S study may help, what can be represented, and how an M&S study can actually help. The customer is also likely to want to know about the modeler's experience and the cost and benefits of previous studies. If the customer is familiar with M&S studies, then the customer may have realistic expectations of the possibilities and the initial conversation can proceed directly to a particular problem, which must be important enough to the customer to warrant an M&S study.

Once a modeler and customer decide to engage in a modeling study, several points are important. The first of these is identifying the stakeholders, including sponsors (those who manage the funding), process or system owners (those responsible for managing the real system or process and the people in it), and the process or system participants (the people who do the work). Beyond a cognizant engineering specialist, stakeholders may include other engineers and scientists in related disciplines using the simulation results, managers and executives deciding on product options, providers of input data, system or product testing, marketing and sales, finance, human resources, investors, government and regulatory agencies, or others impacted depending on the modeling context.

Each stakeholder may have a different perspective on the reality to be represented and the modeler's task is to reconcile their viewpoints using a model. The modeler will have to facilitate discussions that elicit information about the reality in order to represent its structure, its inputs, and its expected and actual outputs. The modeler must also negotiate a model purpose, project budget and schedule, access to each group of stakeholders, access to data, and a model specification including model scope and level of abstraction.

In cases where a modeler has extensive experience in the domain that he/she is modeling, then he/she may not have to rely heavily on domain experts. Usually, though, a modeler who is engaging with a customer must draw heavily upon the experts in the customer organization. The best experts for an M&S study can be those who directly manage the people participating in a system or process because they are the most informed. In an engineering organization, these experts are often technical leads or first-level managers.

Beyond initial sessions in which the modeler elicits information about the system or process, the modeler must ensure that access is available for follow-up discussion of questions that arise during model construction, verification and validation, and experimentation. At the same time, the modeler must keep stakeholders informed of the study and its progress, mindful that stakeholders unfamiliar with M&S may not appreciate the complexity of their own systems and challenges in representing them.

The preceding discussion can be summarized in the following list of questions that must be answered when engaging for an M&S project or study:

- Who are the (groups of) stakeholders and what is the primary interest of each with regard to the modeling project?
- What are the roles of those involved in the project?
- Who will ensure that resources are available for the project or study?
- Who needs to be kept informed of progress and issues?
- Who will the modeler depend on for providing information and quantitative data about the real system or process? What is their availability?
- What sources of data are available?
- How much time is available for the M&S project or study?
- What budget is available for the M&S project or study?

2.3 MODEL SPECIFICATION

Model specification usually begins with identifying a problem and describing its context as a basis for specifying a modeling purpose. The modeling purpose will include the intended audience for the modeling results, the desired set of policies to be simulated, and the kinds of decisions the results are intended to support.

Modeling purposes can be characterized in two dimensions, utility and generality. Three categories of utility are distinguished here.

1. A model can provide an object for discussion as a concept is being defined and social constructs are developed. Conceptual definition models may not go through all the modeling stages, particularly verification and validation, because they serve as conceptual illustrations and support identification of variables that can strongly influence system behavior. Models developed for this first purpose have a very limited life, as they can be thrown away once they have served their purpose, or they may become a basis for more extensive modeling.
2. Models are also built to address a specific problem or question. For example, an organization may want to know how many servers should be specified for a system designed to handle an expected volume of transactions. A model of this kind may be produced for a specific system development project and its usefulness ends with the project, though it can be archived for a later time when a similar project might be undertaken.
3. Models may be developed and maintained for long-term usage. Flight simulators fall into this category. Also in this category are models that represent operations and provide ongoing decision support for operational planning.

In specifying the purpose of a model in the first two categories, it is helpful to pose the single most important question that the model will be used to address. It is also very helpful to establish the graphic that will be used to answer the question, the single most important chart that the customer wants to see. For example, it could be a cumulative distribution function for the time to complete a project, or a quantity distribution function for the number of widgets produced. Whatever it is, it needs to be specified early so that the simulation can be made to produce that chart.

The model may answer questions beyond the most important one originally posed for the model, but the one question helps to focus the model purpose and provides a criterion for model scope decisions. Though a model may have a single, well-defined purpose, it may well provide information on related issues. For example, a model constructed to answer a question about the duration of a process may also indicate what resources are constraining the process. Chapter 7 relates an example illustrating this point.

Modeling purposes in the third category lead to large endeavors that require experience gained from conceptual and limited use models. These types of modeling projects can address multiple purposes difficult to express in a single question. In these cases of larger utility, managing model purpose, scope, and level of abstraction require considerably more coordination and discipline.

Modeling purposes may also be distinguished by their degree of specificity or generality. A model may be built to represent a specific system or process, or a class of systems or processes. General models have much larger audiences than specific models. Very specific models require data from only one source, but general models require data from many sources. Verifying and validating specific models can also require less effort than general models. When specifying the purpose of a model, a modeler should keep in mind that more work comes with greater utility and with greater generality.

The primary modeling purpose question is:

- What question(s) should the modeling results answer?

Model scope may be defined by the modeling purpose, but it is clarified by the boundaries defined for the model. This means that the model must include elements sufficient to generate the outputs of interest. For example, if a customer is interested in resource utilization, then all the demands on the resources should be included. Modeler and stakeholders have to agree on what is included and excluded from the model. Maintaining model scope can be challenging. Stakeholders will have expectations that may go beyond the model scope, so the modeler must remind them of scope and capability. Model scope and boundaries can grow from one model version to the next, but scope should be maintained and clearly communicated for each version.

Modelers face a temptation against good definition. It is the desire to satisfy all stakeholders by providing a model that represents all their perspectives rather than a model that represents a common concern. For example, one stakeholder may want a model that reflects resource usage for a process in order to determine what the capacity of the process is, but another may want a model that includes all the personnel in their organization so that they can see where all their labor is spent, including that spent on the first stakeholder's process of interest. In that case, the modeler may need to use his negotiation skills to facilitate an agreement among the stakeholders for the sake of producing an adequate model within budget and schedule constraints.

The following are model scoping questions:

- Where should the model "start"? Where should it "end"?
- What system elements should be included?
- What resources are to be included?
- For each model component, will inclusion significantly affect the results? If so, will the influence on results be optimistic or pessimistic?
- For each model component, will inclusion strongly affect the model's credibility?
- For each model component, is data available or obtainable? How accurate is it?

Every model is an abstraction of reality and the modeler must choose an appropriate "level" of abstraction for a model. Choosing levels of abstraction can be challenging for a modeler, but it also allows the modeler to control how much detail goes into a model. A good guideline is to model at the level of abstraction necessary to answer the questions. Simple is typically better than complicated. When in doubt, by default start with as simple a model as possible and add detail later as necessary. One technique used successfully by expert modelers is to start with a simple prototype or proof-of-concept model early in the project to work out potential issues with the project, to improve the accuracy of the project time and resource estimates, and to obtain support from the stakeholders.

As an example of level of the abstraction, a model that simulates satellite communications can be very detailed if used to design communication scheduling algorithms, but can be very high level if used to confirm a decision on the number of satellites required in an orbit. The choice of abstraction level is also qualified by an M&S project budget and schedule. A modeler working within a small budget and tight schedule can choose to produce a smaller, more abstract model that requires less work to build and verify than a large, high-fidelity model. In fact, this approach is recommended: if the customer sees that results of a small model are useful, then addition of details for a better fidelity can be negotiated.

The following are model abstraction questions:

- Which of the following factors are influencing the modeling level of abstraction: modeling objective, model scope, performance measures of interest, alternatives to be examined, examination details for alternatives, data availability, execution time, modeling budget and schedule, animation, modeling toolset and language support, and modeler skillset? Is the degree of influence of each factor commensurate with the modeling purpose?
- How should each element be represented and to what level of detail?
- What simplifying assumptions can be made?
- Will any of the assumptions bias the modeling results either pessimistically or optimistically?
- What alternatives are to be explored?
- What scenarios are to be considered?

As a model is specified, important model parameters are discussed. These discussions typically start with output variables that address the modeling purpose and input variables that domain experts recognize as influential. With the discussion of input parameters, sources of quantitative data are discussed. Obtaining data for model parameters can be the most time-consuming part of a modeling project for several reasons. Data for model parameters may not exist and it will need to be elicited or collected. If data does exist, it may be proprietary and 1) upper management will need to be convinced that it should be made available for the modeling project, and 2) a process for acquiring the data will need to be executed. When data is provided, reviewing it and scrubbing it may require substantial effort.

Due to potentially long lead times in obtaining data, discussion of data sources should be undertaken during model specification so that data can be available once a model is constructed. The modeler requires data for model parameters but also for actual outcomes of the subject reality for model validation. Setting up a data collection system may not be feasible within the schedule and budget of the modeling project. If that is the case, then data is limited to whatever is available or whatever estimates can be elicited from domain experts.

The following are data acquisition questions:

- What sources of data are available for model inputs?
- If data is lacking for expected model inputs, can estimates be elicited from domain experts?

- What system performance data can be provided for validating the model?

When modeling a specific system or process, one might attempt to learn the real system or process through documents and telephone interviews. However, trying to model from a distance is difficult and inhibits fair representation of the reality. The best opportunity for good modeling occurs when making site visits, meeting the stakeholders in person, and walking through the subject of the model.

The foregoing discussion can be summarized in the following questions that should be answered when specifying a model:

- What is the question to be answered by a model study?
- What is the intended utility of the model: conceptual definition, solution generation, or long-term support?
- Is the model to represent a specific case or a class of cases?
- What kinds of decisions should be supported by the study?
- Who is the intended audience?
- What set of policies should be modeled?
- What is the model scope?
- What is the model level of abstraction?
- What model outputs are necessary?
- What kind of output data analysis will be necessary?

2.4 MODELING

2.4.1 MODELING PARADIGMS

One of the first decisions to be made in modeling is choosing the modeling paradigm. This may be dictated by the modeler's expertise in a particular paradigm or the paradigms supported by a simulation software package used in the modeler's organization. However, the different paradigms have advantages and limitations for various types of modeling. Continuous modeling, discrete event simulation, and agent-based simulation are discussed here.

Continuous simulation and discrete event simulation are distinguished by their representation of time. In continuous simulation, time is represented in regular intervals. Flows are represented as passing through a continuous model into and out of containers (also called stocks or levels). Flow rates can be increased and decreased based on the variable relationships. With each tick of the simulation clock in a continuous model, a fixed amount of simulated time passes and the values of all model variables, flow rates, and container contents are updated.

In a discrete event model, events are scheduled and the simulation clock moves to each event in the schedule (see the next event time advance approach in Section 3.2.1). Entities move through a model, obtaining resources, spending time in activities, and releasing their resources. Entities can have attributes so that each entity can have its own characteristics. Attribute values are used to set activity durations and to route entities through a model. Variable values are updated with each event.

Because they represent flows, continuous models tend to be more abstract than discrete event models. Where a continuous model treats work as a continuous flow, a discrete event model treats work as individual items passing through activities. Consequently, discrete event model diagrams can be easier to understand for audiences that think of entities being changed through activities performed on them. The ability to characterize entities in discrete event models also adds to representational capability.

Agent-based models represent interacting entities, or agents. Agents have their own characteristics and can initiate actions, communicate with one another, and react to one another. Like discrete event simulation, agent-based models generally treat time as a series of discrete events.

Table 2.1 summarizes characteristics of the three modeling paradigms in terms of system characteristics and modeling goals. Use continuous modeling, such as system dynamics modeling, if a global view is desired and aggregated entities are sufficient, whereby information on individual entities isn't necessary or possible to model. Discrete event modeling is useful for investigating system-level process behavior with visibility into individual entities. Agent-based modeling is also useful for disaggregated modeling whereby individual object behavior can be described and the modeler is interested in collective behavior that emerges from the interactions of the agents.

TABLE 2.1
Model Type Selection Criteria

Criteria	Continuous	Discrete Event	Agent Based
Perspective	Global view with feedback	System-level processes	Individual interacting objects
Entities	Aggregated entities	Disaggregated entities with attributes	Disaggregated agents with behaviors

Having acknowledged the distinctions for modeling paradigms, it is also important to know that current simulation programs are blurring these distinctions, particularly between continuous and discrete event simulation. The programs support both continuous and discrete event timing in the same model and is sometimes called hybrid modeling.

The choice of a modeling paradigm may depend on the simulation capabilities required as well as the modeler's expertise. These three modeling paradigms are discussed in more detail in Chapter 3.

2.4.2 MODEL CONSTRUCTION

Once a modeling paradigm and supporting software have been selected, decisions must be made about representing the real subject of the model. For continuous models, anything in the real system that changes is represented as a flow, so one must decide what flows to represent, how they are modified, and how they interact. For discrete event models, one must decide how to represent system elements using entities and resources, and how entities are routed. For agent-based models, agents are identified, their characteristics are specified and rules for their behavior are written.

In making decisions about model structure, multiple representational possibilities may be available. Consider, for example, modeling of a workflow process in a discrete event model. Entities may be used to represent work items and people are treated as resources, or entities may represent people who perform work and the work items are treated as resources. The choice of representation may depend on the modeling purpose. If the stakeholders are interested in changes in the people as they work, then the people can be characterized using attributes and attribute values that are updated to reflect changes in personal characteristics. On the other hand, if the stakeholders are interested in changes in work products and work capacity, then work items can be represented as entities with attributes, and people are the resources. When representational choices become apparent, simple trial models of each should be produced and evaluated.

Another structural decision in modeling is the division of the model into parts. Small models may not need partitioning, but larger models are managed best in parts. A number of factors may influence decisions about partitioning a model. The real system may logically be partitioned, suggesting the way in which a model of it should be partitioned. Also, the different flows or entity types or agents identified for a model may suggest partitions. Previous models of the subject reality may also suggest advantageous or disadvantageous ways to partition a model. In some cases, partitions are created to add new purpose and scope to an existing model.

As construction proceeds, a modeler should distinguish between design and implementation. For those who use graphical simulation software, the difference between design and implementation can be blurred because part of a model can be a working implementation while another part is being designed. A temptation faced by all modelers, especially novices, is to create an entire design of a large model in a graphical program with the expectation that the model runs as intended. However, the result can be an unwieldy model that is difficult to debug. When such a model has been created, it is recommended that it be treated as a design, set aside, and start a new model in which small sections can be implemented and tested, one section at a time. Of course, this iterative approach can and should be used from the outset, designing and implementing in pieces. An iterative approach with successive elaborations ("build a little, test a little") is best.

As a model is constructed, it should have only enough detail to address its purpose(s) and no more. Modelers face several temptations that can lead to models that are larger than necessary:

- The desire to have the most comprehensive model in the field, one that represents all relevant phenomena known on the subject.
- The desire to satisfy all stakeholders, who may be asking questions such as "Does it include ... ?" and "Can it show ... ?"
- The desire to build and maintain only one model that incorporates all subsystems or incorporates all system variations.
- The desire to avoid representational abstractions about which one is unsure. It can seem easier to add many details and be sure that the representation is correct rather than try more abstract representations that require less data and testing.

As these temptations arise, it is best to face each one and acknowledge the trade-offs that come. As models grow, so does the amount of work in constructing, testing, fixing, and managing them.

Depending on how a model is to be used, performance requirements may be necessary. Iterative construction also facilitates assessment of model performance as the model is being built. For example, if many thousands of runs are needed to produce the necessary output data, then the simulation software must be able to record all the runs without using all available computer memory. The model must also be able to run fast enough to produce the required number of runs in a reasonable time period. Performance requirements and desires should be documented and performance should be assessed periodically during model construction to determine whether computing resources are sufficient.

Iterative construction also facilitates configuration management of a model. As each addition is made to a model, the change can be documented either in the model file or a separate document. The model file can be copied to a new file and a new edition can be started. This management of configurations is especially helpful when experimenting with model constructs and wanting to branch from a previous version, when multiple modelers are working on the same model, while debugging and looking for the source of a problem, or when stakeholders are requiring results and a stable version is needed for producing them.

Modeling decisions can reflect trade-offs between multiplicity and behavioral complexity. For example, suppose a factory has multiple product assembly lines that have much in common but differ from one another in a few processing steps. A graphical model of these lines might depict each line separately or it might abstract from the separate lines by combining them into a single line with processing exceptions to represent the differences. Combining the lines produces a simpler static view of the model. However, all the items passing through one processing line can make tracing more difficult than tracing fewer entities through individual lines. In the end, one may decide to use a graphical depiction of multiple lines because the diagram is easier to use when discussing the model with stakeholders familiar with the factory layout.

2.4.3 DATA COLLECTION AND INPUT ANALYSIS

Parameter creation is part of model construction. Parameters for inputs and outputs should be readily identifiable to system managers and participants. Input parameters should be created with the expectation that data can be collected for them and output parameters should be created with the expectation that data from system outcomes is available for validation.

Data must be relevant and of good quality. Relevant data comes from measurements that have the same meaning and units as the model parameters for which the data will be used. Good quality implies that data is complete and does not contain anomalies, such as inaccurately recorded values. Obtaining good-quality, relevant data for input parameters and for validation can be challenging. Although some types of simulation models are built to use qualitative data, simulation models ordinarily use quantitative data.

Quantitative data can be deterministic or stochastic. Deterministic data can be either constant values or variable values computed as a function of time or other independent variables. Stochastic data reflects variation that cannot be characterized as a deterministic function. The uncertainty in values can be characterized in a random distribution. When recorded data is provided for input parameters, it can be analyzed to determine whether it should be used in a model as constant, functionally variable, or randomly variable. However, when recorded data is not available for input parameters, the modeler faces a question as to whether data should be collected or elicited.

If data collection is undertaken, the costs of developing a measurement system and collecting data are incurred. These include specifying the data to be collected, specifying the collection methods and instruments, providing for data storage, training data recorders, and reviewing the collected data for completeness and anomalies. The time and expense required for data collection may not be feasible for a modeling project, especially for initial models of a system. In these cases, elicitation of parameter values from domain experts should be considered.

Occasionally domain experts can offer constants or functions for parameter values, but usually recalling values from experience will produce estimates with variation. When consulting experts in a system or process, they can be asked for a most likely value of a parameter, a minimum value, and a maximum value. The definition of minimum and maximum can lead to debates as to whether these mean extreme values (the lowest and highest values either seen or possible) or "90% values." One way to facilitate this discussion is to ask for low and high values as usually occurring and then ask whether extremes beyond the usual lows and highs can appear. The following series of questions is helpful for eliciting data for each parameter.

- What is the lowest value of the parameter most of the time?
- What is the highest value of the parameter most of the time?
- Is a value between these two more likely than either one? If so, what is it?
- If the parameter has a most likely value, can values occur that are less than the lowest value or more than the highest value?

Once data is obtained for model inputs, it must be analyzed to produce input values. Input analysis can involve a number of statistical tools, and it is the subject of Chapter 5. It will elaborate more on input analysis methods, including using the answers to the preceding questions. It is sufficient to say that input analysis is another step involved in model iteration. Much effort can be spent choosing input values including input distributions. The best approach in many cases is to apply just enough effort to obtain input values that are good enough to test a model with runs for a sensitivity analysis. The sensitivity analysis varies the input values systematically so that the relative influence of inputs can be estimated. With these estimates, a modeler can decide which inputs deserve further effort for refinement.

2.5 MODEL ASSESSMENT

When a model has been produced, stakeholders call upon the modeler(s) to explain the model's credibility. The modeler must establish his/her own confidence in the model and then convey that confidence to stakeholders and peers, usually through sharing results of Verification and Validation (V&V) exercises. Verification exercises determine whether or not a model is built correctly (error-free) and represents the intended behavior according to the model specification. Validation exercises determine whether the model provides an adequate representation of the real system for the model's stated purpose and addresses the sponsor's problem. The importance of model assessment cannot be understated: stakeholders must have confidence in a model in order to use its results well.

Most textbooks on M&S cover model assessment. Richardson and Pugh, in their text on system dynamics modeling [25], present a model assessment scheme summarized in Table 2.2 that distinguishes exercises for structural assessment and behavioral assessment. They also add model evaluation exercises to the V&V exercises in their scheme outlined below. This assessment scheme is also covered in more detail in modern treatments of system dynamics including [29] and [18].

The details of these assessments are listed below:

- Verification of structure
  - Equation review is a modeler check of every equation for correctness. The parameter dimensions of each equation are analyzed for potential errors. Each equation is checked for the effects of extreme values, including division by zero.
  - Structural adequacy review is a modeler review to ensure that the elements included in the model and the level of abstraction are sufficient to address the model's stated purpose and specification.
- Verification of behavior
  - Traces of specific entities are essential to verifying a model's logic and the correctness of its implementation. Tracing should cover each path and test execution of each condition.

TABLE 2.2
A Model Assessment Scheme (adapted from Richardson and Pugh [25])

	Structure	Behavior
Verification	Equation review Structural adequacy review	Parameter variability testing Structural insensitivity review Traces
Validation	Face validity review Parameter validity review	Output comparisons Outputs discrimination check Case replication Case prediction
Evaluation	Model appropriateness review	Sensitivity analysis Unexpected behavior review Anomalous behavior review Extreme inputs review Process insights review System improvement test

- Parameter variability testing is testing that model outputs reflect changes to model inputs in the same way that the real system outputs reflect changes to real system inputs.
- Structural insensitivity review is an expert review of model outputs and behavior against its structure to ensure that the level of abstraction does not inhibit the modeling purpose.

- Validation of structure
  - Face validity is assessed by expert review of the model structure to confirm that, for the modeling purpose, it is an adequate representation of the real system.
  - Parameter validity is assessed by expert review of parameters to ensure that they are recognizable and not contrived, and that parameter values represent the best available information about the real system.
- Validation of behavior
  - Comparisons of model outputs and system outputs are made statistically. System output values should fall within confidence intervals on the mean model outputs.
  - Experts comparing system outputs and model outputs should not be able to discriminate between the two.
  - A case replication demonstrates the model's ability to imitate real system results.
  - A case prediction demonstrates the model's ability to forecast system behavior accurately. This may be a statistical test in which a prediction

  interval is constructed and system output is tracked to see whether it falls within the interval.
- Evaluation of structure
  - Members of the intended audience review the model for appropriate levels of abstraction/detail and simplicity/complexity.
- Evaluation of behavior
  - Sensitivity analyses can be run using designed experiments to identify the relative influence of input variables on each outcome, as well as interactions between inputs. The results should be useful in explaining some phenomena in the real system.
  - A modeler reviews any unexpected behavior found during model usage and performs traces to explain the behavior. If possible, the behavior should be observed in the real system.
  - If the model exhibits anomalous behavior, it should be reviewed against the real system to ensure that it does not conflict with system behavior.
  - When extreme values are input to the model, model behavior should imitate system behavior when the system is subjected to the same inputs.
  - Review model usage and record any insights gained about system behavior.
  - A system improvement test considers whether the model identifies any system improvements.

Most, but not all, of the foregoing exercises are necessary for building confidence in a model. The verification exercises are essential for the modeler's confidence that a model works correctly. The tracing is especially important so that a modeler can explain the inner workings when called upon to do so. Fortunately, verification exercises can be run iteratively during model construction so that they are not all left until afterward (when stakeholders are calling for modeling results they can use).

Validation and evaluation of structure starts with the first time a modeler presents a draft model to stakeholders, explains it to them, and elicits their feedback. This feedback usually helps correct and refine model structure as well as facilitate further data collection. In such a meeting, the model specification can be refined, data collection can continue, and model structure can be validated.

Validation and evaluation of behavior exercises provide a number of opportunities for demonstrating what a model can do. The exercise that stakeholders request most often is replication of a case of actual results. Therefore, early in the modeling process, a modeler should be looking for a case of recent system behavior that the model can be calibrated to imitate. In the course of such a calibration, if the modeler cannot reproduce one or two primary system outcomes, then the modeler must reexamine data and assumptions, sometimes returning to system experts. For example, it can happen that elicited values for a parameter were inaccurate and that trying new values allows the model to reproduce system outputs. If the experts agree that the initial values may have been erroneous and that new values are better, then the modeler has leeway for calibration.

The foregoing example also illustrates occasions in which a model is like a puzzle: the modeler obtains all the pieces and puts them together. If they do not fit (i.e., outcomes do not imitate real system behavior), then the modeler must figure out which piece(s) do not fit well and scrutinize them with experts. They may find that they tried to insert the wrong piece into the puzzle.

2.5.1 EXPERIMENTATION AND OUTPUT ANALYSIS

As a model is assessed, experimentation and output analysis can begin in earnest. Good evaluation exercises usually signal the start of experimentation and provide the model with insights for further experimentation. Unfortunately, too many models are not used often enough for experimenting, sometimes because the modeler lacks the imagination to create experiments or statistical knowledge and skills to conduct experiments. Modelers are encouraged to put as much effort into using a model as they put into making it.

One school of thought on simulation is that M&S is a learning tool for investigating how systems work. They measure success from what one can learn through M&S. Another school of thought views M&S primarily as a statistical tool that produces quantitative data to support decision making. The two schools of thought are not mutually exclusive, as indicated in the discussion on model specification. Models can have a range of utility and a particular model can evolve from a simple learning model to a decision support model.

Like input analysis, output analysis usually involves statistical analysis of output data and presentation of the data in formats accessible by the stakeholder audience. Analyzed outputs should be used to tell a story and provide information that addresses the problems about which stakeholders are thinking.

2.6 MAKING RECOMMENDATIONS AND REPORTING

As a modeler exercises a model, generates output data, and analyzes it, model behaviors are revealed and he/she comes to understand how a model works. This information provides a basis for discussions with system participants who can apply their knowledge of system workings. System participants often know about the behavior a model describes but the modeler can clarify and quantify the behavior. When they find behavior that is counterintuitive or issues that are unexplained, the modeler is provided opportunities for investigation by running model scenarios.

Recommendations can also emerge from these conversations. Participants often have ideas that they think should be implemented for improving the way a system or process works, and the modeling results may indicate which ideas are most useful. In exploring alternative scenarios, the modeler may also see improvement opportunities that participants had not seen.

Insights and recommendations should not come as surprises to stakeholders. Those surprised by recommendations may be reluctant to accept them. Ongoing discussions should lead up to the final report and briefing with its recommendations.

Good documentation of an M&S study is important for facilitating understanding of the results, especially among those not directly involved in the study, and promoting their implementation. Though a model may not be used by stakeholders, making it accessible confirms transparency of the study. an M&S study report should include a clear description of the problem and the appropriate view of the system, the objectives of the study, modeling specification and assumptions, the modeling process, an overview of the model, the model assessment activities and results, and conclusions with recommendations. The following outline may be used as a checklist for an M&S report.

1. Introduction
   - Problem statement and description
     - Extent and history of the problem, causes of the problem, possible solutions and their obstacles
   - Purpose of study
   - Purpose of model building
   - Executive summary of key results
2. Background
   - System description
     - Diagrams that illustrate the system configuration
   - System reference behavior
     - Narrative description, tabular data, graphs
   - Assumptions and the underlying rationale for each
3. Model Development
   - Modeling process
     - Modeling approach and sequence of events
   - Model evolution
   - Data acquisition
     - Source of data, method of collection, problems, solutions, analysis, etc.
4. Model Description
   - Time frame, spatial boundaries, entities, attributes, key assumptions
   - Process flow and model structure
     - Flowcharts, model diagrams, etc.
   - Key logic and equations, sources of uncertainty, probability distributions, etc.
   - Model Overview
     - Sources of data and input analysis
     - Flowcharts, flow networks, block diagrams, etc.
   - Assumptions and other model details
   - Approach for verification and validation
5. Model Verification and Validation
   - Testing results, extreme values, sensitivity analysis
   - Comparison to reference behavior, expert review, etc.
   - Statistical analyses

- Other testing and V&V methods
6. Model Application and Transition
   - Experimentation and analysis of results
   - Tabulated data, plots, bar graphs, histograms, pie charts, statistical analyses and other reports, etc.
   - Interpretation of model results
   - Limitations of the model and future enhancements
   - Next steps
   - Model transfer issues
     - Availability of model user documentation and of model developer documentation
7. Conclusions and Recommendations
   - Real-world system
     - Policy suggestions
   - Future model usage and development
   - Modeling process notes
   - Modeling tool(s) and platform used
   - Process improvement scenarios
   - Future research
8. Appendices (if necessary)
   - Supplementary model details
   - Model run output
   - Selected computer outputs, related letters, technical articles, etc.
   - Additional data analysis as needed

2.7 KNOWLEDGE AND SKILLS FOR MODELING AND SIMULATION

The discussion in this chapter should have made clear that M&S requires knowledge and skills, so this last section discusses these areas explicitly. A modeler must possess knowledge and skills in four areas. First, one must understand modeling and simulation concepts, processes, paradigms, and tools as described in this chapter. M&S tools are numerous and are evolving, and full descriptions are beyond the scope of this book. Reviews and surveys of simulation software are readily available online. An example survey of tools kept updated is at `http://www.orms-today.org/surveys/Simulation/Simulation.html`.

The second area in which a modeler requires knowledge is that of the domain being modeled. The domain might be distinguished in two degrees of relevance: specific systems and fields. A modeler who is familiar with specific systems may also be a domain expert capable of modeling with minimal reliance on other system experts. A modeler who is expert in a field, for example product development, and is asked to model a specific development program must rely heavily on experts in the development program to acquaint him/her with its specific structure and data. In this case, a modeler brings familiarity with the structure and dynamics of product development as well as expertise in representing them. Sometimes a modeler is requested for his/her M&S skills despite a lack of familiarity with a field. In this case, he/she may learn from published modeling work in the field, but is still more reliant on domain experts to learn about the field and the subject system or process in sufficient depth for modeling.

Engagement skills are a third area in which a modeler should be well-versed. This area includes human relations, organizational, and project management skills that enable a modeler to meet with potential customers; assess their needs and relate them to possible M&S solutions; develop reasonable expectations for an engagement; negotiate a program of study; work with participants to specify a model, collect data, and validate the model; keep sponsors informed; and report useful results.

The fourth M&S knowledge and skill area for modelers is statistics. Models are essentially quantitative tools executed on computers and the success of most M&S studies depends on quantitative analysis. Input values are usually the result of statistical analysis, such as distribution fitting. Model experimentation and sensitivity analysis often require designed experiments that are analyzed with analysis of variance (ANOVA). Outputs may also need to be analyzed with hypothesis testing, regression analysis, confidence intervals, and prediction intervals. The modeler uses statistics to understand system behavior as represented in a model and relate a story of that behavior to stakeholders. See statistics details in Chapters 4, 5, and 6.

In summary, keys to a successful M&S project include a well-defined and achievable goal, complementary skills on the project team, an adequate level of user participation, selection of an appropriate simulation toolset or language, and effective project management.

2.8 SUMMARY

Modeling and simulation (M&S) projects vary widely, so modeling processes and methodologies can be employed very differently across projects. The nominal modeling stages are engagement, specification, construction, verification and validation, experimentation, and reporting. But the modeling process does not proceed through these stages in a strictly sequential manner because a modeler undertakes combinations of these stages iteratively. A modeler needs specialized knowledge and skills to conduct a modeling process well.

First, one should identify the stakeholders including sponsors, process or system owners, and the process or system participants who do the actual work. Stakeholders may also include other engineers and scientists in related disciplines using the simulation results. The modeler must always keep stakeholders informed of the study and its progress.

Model specification begins with identifying a problem and describing its context for a modeling purpose. The purpose will include the intended audience for the modeling results, the desired set of policies to be simulated, and the kinds of decisions the results are intended to support. The modeler must choose an appropriate level of model abstraction necessary to answer the questions. By default start with a simple model and add detail as necessary.

One of the first decisions in modeling is choosing the modeling paradigm. The different paradigms of continuous modeling, discrete event simulation, and agent-based simulation have respective advantages and limitations for various types of modeling.

Continuous models are usually more abstract than discrete event models. Use continuous modeling if a global view is desired and aggregated entities are sufficient. Discrete event models can be easier to understand for audiences that think of entities being changed through activities performed on them, and useful for investigating system-level process behavior with visibility into individual entities. Agent-based modeling is also useful for disaggregated modeling whereby individual object behavior can be described and if one is interested in collective behavior that emerges from their interactions. The choice of modeling paradigm may also depend on required simulation capabilities and the modeler's expertise.

During model construction, decisions must be made about representing the real-world subject. For continuous models, one must decide what flows to represent, how they are modified, and how they interact. For discrete event models, one must decide how to represent system elements using entities and resources, and how entities are routed. For agent-based models, agents are identified, their characteristics are specified, and rules for their behavior are written.

Another structural decision in model construction is the partitioning of a model. An iterative approach with successive elaborations ("build a little, test a little") is best to support these modeling decisions. Iterative construction also facilitates assessment of model performance as it is being built, and configuration management of the ongoing model changes.

For data collection and input analysis, the input parameters should be created such that the data can be collected and outputs defined that will be available for validation. The costs of data collection should be considered, and elicitation of parameter values from domain experts may be warranted.

Model assessment addresses 1) verification to determine whether or not a model is built correctly without errors and represents the intended behavior according to the model specification, and 2) validation to determine whether the model provides an adequate representation of the real system for the model's stated purpose and addresses the sponsor's problem. V&V covers both structural and behavioral aspects.

Experimentation and output analysis can begin when a model is being assessed. Like input analysis, output analysis involves statistical analysis of output data and presentation of it to the stakeholder audience such that it addresses their problems.

Good documentation of an M&S study is important for facilitating understanding of the results, especially among those not directly involved in the study, and promoting their implementation.

A modeler must possess the right knowledge and skills to conduct a good simulation study. One must understand M&S concepts, processes, paradigms, and tools; have knowledge of the application domain; engagement skills to work with people; and statistics skills for the quantitative analysis.

The overall keys to a successful M&S project include a well-defined and achievable goal, complementary skills on the project team, an adequate level of user participation, selection of an appropriate simulation toolset or language, and effective project management.