INTRODUCTION TO MODEL BUILDING

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Abstract

The building of simulation models is both an art and a science. The following paper trys to provide guidance to the model builder during the design and implementation process.

INTRODUCTION

There is little question that simulation is one of the most powerful analysis tools available to those responsible for the design and operation of complex processes or systems. Simulation is the process of designing a model of a real system and conducting experiments with this model for the purpose either of understanding the behavior of the system or of evaluating various strategies for the operation of the system. The concept of simulation is both simple and intuitively appealing. It allows the user to experiment with systems (existing or proposed) where it would be impossible or impractical otherwise. Unfortunately, its use also presents the potential for disaster. John McCleod compared simulation to the scalpel used by a surgeon. Used in skilled hands it can accomplish tremendous good, but it must be used with great care and by someone who knows what they are doing.

Weinberg (1) pointed out that some systems thinkers view simulation as the ultimate tool because the way to demonstrate understanding of behavior is to construct a system (or model) that exhibits that behavior. There are three goals or purposes to simulation models:

1. Improving thought processes by making thoughts explicit and by posing sharp questions.
2. To solve specific problems related to the systems of interest.
3. Use the model to predict future behavior, that is, the effects that will be produced by changes in the system or in its method of operation.

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THE MODELING FRAMEWORK*

The simulation modeling framework consists of six elements: (1) the real system, (2) the conceptual model (our perception of the real system), (3) the experimental domain, (4) the formal model, (5) the computer implementation or computer model, and (6) the experimentation. By the real system we mean that there is an entity, situation, or system which has been selected for analysis. We also mean that there is a method of isolating out a part of reality, labeling it a real system and collecting information and data about it. The real system is nothing more than a source of potentially acquirable data. At any point in time we will have acquired only a finite sub-set of this data from what is an infinite set or universe. In general, the real system is (or will become) a source of behavioral data consisting of time-based trajectories of input, state and output variables.

The conceptual model is the model builder's perception and understanding of the real world system. Here, the modeler is defining the boundaries, components, descriptive variables and interactions which are believed to describe the real system. The conceptual model consists of a hypothetical, complete explanation of what the real world system consists of and how it functions.

The experimental domain, characterizes a limited set of circumstances under which the real system is to be studied. Here we are concerned with the specification of the goals and purpose of the study. It is a prescription of the conditions for which the formal model is intended to match reality. The explicit purpose of the model has significant implications for the whole model building, validation and experimentation process. For example, if the model's goal is to evaluate a proposed or existing system in an absolute sense, this imposes a heavy burden upon the accuracy of the model and demands a high degree of isomorphism. On the other hand, if the goal is the relative comparison of two or more systems or operational procedures, the model may be valid in a relative sense even though the absolute magnitude of responses varies from that which would be encountered

* Based upon B. P. Zeigler, Theory of Modeling and Simulation, Wiley & Sons, NY, 1976.

Model Building (continued)

in the real world. It is not surprising then to learn that a model may be valid in one experimental domain but invalid in another. Thus there may be many valid models (at least one for each experimental domain). The experimental domain also specifies the resource constraints under which the study is to be conducted such as schedule, manpower and dollar limitations.

In most cases, the great complexity of the conceptual model precludes its consideration as a possible simulation model due to resource limitations. Fortunately, because of the selection of a particular experimental domain, the modeller can likely construct a relatively simple formal model (also called the lumped model) that is valid in that domain. The formal model takes the form of logic flow diagrams, equations, etc. which describe the governing relationships that determine the behavior of the system. In principle, the modeller simplifies by aggregating or lumping together components and elements that are strongly connected through structure, function or both. By lumping together components and simplifying interactions, hopefully a model results that neither oversimplifies the system to the point where the model becomes trivial nor carries so much detail and complexity that it becomes intractable and prohibitively expensive to run. In the formal model we purchase ease of manipulation at the cost of a certain loss of complexity and detail of content. One of the laws of science is, "If we want to learn anything, we must not try to learn everything." This is called the Lump Law by Weinberg (1).

The next step is to write the step-by-step instructions for implementation of the formal model upon a computer. The computer program implementing a formal model should not be identified as the model itself. Different programming languages encode the same model in different ways and will produce different behavior. Great care must be taken to insure that the computer model or program behaves as the modeller intended.

Finally, the computer program is used to generate model behavioral data through planned experimentation and the results analyzed. In this stage there are also numerous pitfalls awaiting the unwary. Depending upon how the experiments are conducted and analyzed, erroneous conclusions can be drawn.

THE SIMULATION PROCESS

There are a number of excellent introductory books dealing with the methodology of simulation (2-7). We will therefore present the process in outline form. The following stages may be distinguished:

1. System (or process) Definition--Determining the boundaries, restrictions and measures of effectiveness to be used in defining and studying the system (or process).
2. Model Formulation--Reduction or abstraction of the real system to a block or logical flow diagram.
3. Data Preparation--Identification of the data needed by the model and their reduction to an appropriate form.
4. Model Translation--Description of the model in an appropriate language acceptable to the computer to be used.
5. Validation--Determining that any inferences drawn from the model about the real system will be correct to some acceptable level of confidence.
6. Strategic Planning--Designing an experiment that will yield the desired information.
7. Tactical Planning--Determining how each of the test runs specified in the experimental design is to be executed.
8. Experimentation--Execution of the simulation to generate the desired data and to perform sensitivity analyses.
9. Interpretation--Drawing inferences from the data generated by the simulation.
10. Implementation--Putting the model results to use.
11. Documentation--Recording the project activities and results as well as documenting the model and its use.

PROBLEM AND MODEL DEFINITION

To find an acceptable or optimal solution to a problem one must first know what the problem is. Thus analysis begins with the specification of the system of interest, the environment in which it exists and operates, the specification of goals of the system and the purpose of the study.

In the process of studying a system or process and converting the resulting knowledge into a mathematical model, we must specify the:

1. purpose of the model.
2. components to be included in the model.
3. parameters and variables associated with the components.
4. functional relationships among the components, parameters, and variables.

Simulation experiments are conducted for a wide variety of purposes, some of which are:

1. Evaluation--determining how good a proposed system design performs in an absolute sense when evaluated against specific criteria.

2. Comparison--comparing competitive systems designed to carry out a specified function, or comparing several proposed operating policies or procedures.

3. Prediction--estimating the performance of the system under some projected set of conditions.

4. Sensitivity analysis--determining which of many factors are the most significant in affecting overall system performance.

5. Optimization--determining exactly which combination of factor levels will produce the best overall response of the system.

6. Functional relations--establishing the nature of the relationships among one or more significant factors and the system's response.

After we have specified (at least tentatively) the specific goal or purpose for which the model is to be constructed, we begin to identify the pertinent components. This process entails itemizing all the components of the system that contribute to the effectiveness or ineffectiveness of its operation. Once a complete list of the components of a system is specified, we next determine whether each component should be included in our model. This is easier said than done, since at this stage of model development it is not always clear whether a component is significant to the overall goal. One of the key questions to be answered is whether a particular component is to be considered part of the model or part of the environment.

Once we have decided which components and variables we shall include in our model, we must then determine the functional relationships among them and the values of the parameters to be used. Again, formidable problems confront us. First, it may be difficult (if not impossible) to quantify or measure certain variables that are important to the behavior of the system. Second, the relationships between components and variables may not be clear. Third, the data and information we need may not be available, or perhaps not exist in the form we need. Thus, decisions regarding the data to be used and their validity, form, and goodness of fit to theoretical distributions and past performance, are all critical to the success of the simulation experiment, and far from being academic points.

Having specified the goals and objectives of the study and defined the system, we next reduce the real system to a logical flow diagram or static model. We wish to construct a model of the real system that neither oversimplifies the system to the point where the model becomes trivial (or worse, misleading) nor carries so much detail that it becomes clumsy and prohibitively expensive. The danger is that the model may tend to be too detailed and include elements which contribute little or nothing to the understanding of the problem.

The tendency is nearly always to simulate too much detail rather than too little. Thus, one should always design the model around the questions to be answered rather than imitate the real system exactly. Pareto's law says that in every group or collection there exists a vital few and a trivial many. Nothing really significant happens unless it happens to the vital few. The tendency among systems analysts has too often been to transfer all the detailed difficulties in the real situation into the model, hoping that the computer would solve their problems. This approach is unsatisfactory not only because of the increased difficulty of programming the model and the additional cost of longer experimental runs, but also because the truly significant aspects and relationships may get lost in all the trivial details. Therefore, the model must include only those aspects of the system relevant to the study objectives.

PROGRAMMING LANGUAGES

Early effort in a simulation study is concerned with defining the system to be modeled and describing it in terms of logic flow diagrams and functional relationships. But eventually one is faced with the problem of describing the model in a language acceptable to the computer to be used. Unfortunately, so many general and special purpose programming languages have been developed over the years that it is nearly impossible to decide which language best fits or is even a near best fit to any particular application. There were over 170 alone in 1972 and new ones are being developed every day (8).

Any algorithmic programming language can be used for simulation modeling, but those languages designed specifically for the purpose of computer simulation provide certain useful features. These include:

1. Reduction of the programming task.

2. Provision of conceptual guidance.

3. Aide in defining the classes of entities within the system.

4. Flexibility for change.

5. Provide a means of differentiating between entities of the same class by characteristic attributes or properties.

6. Relate the entities to one another and to their common environment.

7. Adjust the number of entities as conditions vary within the system.

The most widely used simulation languages are GPSS (9), SIMSCRIPT (11), GASP-IV (12), SLAM (21), and in Europe, SIMULA (13).

One of the most exciting recent developments is the appearance of languages which allow discrete, continuous or combined models. GASP-IV, SIMSCRIPT, SLAM, and more recently SIMAN allow a great deal of flexibility to the modeller.

VERIFICATION AND VALIDATION

The next general problem is how to bring to an acceptable level, the users' confidence that any inference about a system derived from the simulation is correct. Basically, three questions are of concern:

1. Does the model adequately represent the real world system?

2. Is the model generated behavioral data characteristic of the real system behavioral data?

3. Does the simulation model user have confidence in the model's results?

Consequently, we are concerned with tests that fall into three groups: tests of model structure, tests of model behavior and tests of the policy implications of a model.

We will use the terms verification and validation in the sense used by Fishman and Kiviat (14). Verification entails the comparison of a model to empirical reality. In verification, the model structure may be compared directly to descriptive knowledge of the real system structure or model behavior may be compared to observed real system behavior. Validation on the other hand is the process of establishing confidence in the soundness and usefulness of the model's output. A model is created for a specific purpose, and its adequacy or validity can only be evaluated in terms of that purpose. The goal is to generate a model that creates the same problem and behavior characteristics as the process or system being studies. Validation is a continuous process, beginning with the start of the study, that continues as the model builder accumulates confidence that the model behaves plausibly and generates problem symptoms or modes of behavior seen in the real system. Validation then expands to include persons not directly involved in constructing the model. At this point we can further clarify the distinction between verification and validation. While verification is an activity entailing comparison of a model to empirical reality, validation is a communication process that requires the model-builder to communicate the bases for confidence in a model to a target audience. Unless the modeler's confidence in a model can be transferred, the model's usefulness will never be realized. Thus through verification testing, the model builder develops personal confidence in the model and through validation measures, transfers that confidence to others.

It is important to realize that validation should be considered one of degree and not an either-or notion; it is not a binary decision variable where the model is valid or invalid. There are no one or two tests which will serve to validate a simulation model, rather, confidence in the usefulness of a model must gradually accumulate as the model passes more tests and as new points of correspondence between model and empirical reality are examined. Testing goes on continuously in the process of constructing and using the model.

Validation must be considered from three different perspectives: (1) the model builder, (2) the technical evaluator, and (3) the non-technical model user. Only the model builder has the capacity to conduct all of the confidence building tests. The technical evaluator (generally a supervisor) is usually limited to reviewing the information and technical data provided by the modeller. The non-technical user rarely has the technical background or mathematical sophistication to be able to understand the verification tests conducted. Yet ultimately, all three levels must be convinced of the model's validity if its results are to be used.

The process of verification and validation entails our trying to preclude making one or more of the following types of errors:

1. Errors in definition and perception of the real world system.

2. Errors in design of the model.

3. Errors in the data used.

4. Errors in programming.

5. Errors in procedure or use of the model.

6. Errors in interpretation of the results.

DESIGN OF EXPERIMENTS

We have defined simulation as being experimentation via a model to gain information about a real world system. It then follows that we must concern ourselves with the strategic planning of how to design an experiment that will yield the desired information. The design of experiments is a topic whose relevance to simulation has long been acknowledged but rarely applied in practice. The design of a computer simulation experiment is essentially a plan for purchasing a quantity of information which may be acquired at varying prices depending upon the manner in which the data are obtained. Since the first publication in 1935 of R. A. Fisher's book, The Design of Experiments, a great number of books and papers on experimental design have appeared and the use of designed experiments has found widespread application. The purpose of using these designs is twofold: (1) they are economical in terms of reducing the number of experimental trials required and, (2) they provide a structure for the investigator's learning process. The running of a simulation experiment is the process of exercising or running the model so as to observe and analyze the resulting information to obtain the desired answers. The experimental design identifies a particular approach for gathering the information needed to allow valid inferences to be drawn.

Depending upon the specific purpose of the experimenter, there are several different types of analysis which may be required. Among the more common are:

1. Comparison of means and variances of alternatives.

2. Determining the importance or effect of different variables and their limitations.

3. Searching for the optimal values of a set of variables.

Designs to accomplish the first type of analysis are generally called single-factor experiments and are fairly straightforward, with the major concerns of the experimenter being such matters as sample size, starting conditions, and the presence or absence of autocorrelation. The second type of analysis is one toward which most textbooks on design and analysis of experiments are directed. These designs primarily utilize analysis of variance and regression techniques for the interpretation of the results. The third type of analysis usually requires search techniques of experimentation.

TACTICAL PLANNING

In general, tactical planning involves questions of efficiency and deals with the determination of how each of the test runs specified in the experimental design is to be executed. Primarily, tactical planning is concerned with the resolution of two problem areas: (1) starting conditions, as they affect reaching equilibrium, and (2) the need to reduce the variance of the answer as far as possible while minimizing the required sample sizes.

The first problem (i.e., starting conditions and their effect upon reaching equilibrium) arises from the artificial nature of model operation. Unlike the real world the model represents, a simulation model operates only periodically. That is, the experimenter starts the model, obtains his observations, and shuts it down until the next run. Each time a run is started, it may take a certain period of time for the model to reach equilibrium conditions representative of the real world system operations. Thus, the initial period of operation of the model is distorted owing to the initial start up conditions. The solution is to (1) exclude data for some initial period from consideration, and (2) choose starting conditions that reduce the time required to reach equilibrium. Reasonable starting conditions can reduce but not eliminate the time required for the simulation model to approach equilibrium conditions. Therefore it is still necessary to determine when measurement should begin.

The second part of the tactical planning problem deals with the necessity to estimate the precision of experimental results and the confidence attributable to the conclusions or inferences drawn. This immediately brings us face-to-face with such areas as variability, sample size, and replication. In any experiment, we try to obtain as much information as possible from a limited amount of experimentation. Several techniques for reducing the variance of response have been proposed (mostly in connection with survey sampling procedures), which can significantly reduce the required sample size and number of replications of the experiments. The use of very large sample sizes can overwhelm virtually all the tactical problems of simulation but usually at a great cost in computer and analysis time. The more complex the simulation model, the more important is good tactical planning before running the experiments.

EXPERIMENTATION AND SENSITIVITY ANALYSIS

Ultimately, after all development and planning, we run the model to obtain the desired information. At this stage, we begin to find the flaws and oversights in our planning, and to retrace our steps until we achieve our originally established goals.

Sensitivity analysis is one of the most important concepts in simulation modeling. By this we mean determining the sensitivity of our final answers to the values of the parpmeters used. Sensitivity analysis usually consists in systematically varying the values of the parameters over some range of interest and observing the effect upon the response of the model. In almost any simulation model, many of the set variables are based upon highly questionable data. In many cases, their values may have been determined solely upon the best guess of experienced personnel or very cursory analysis of minimal data. It is therefore extremely important to determine the degree of sensitivity of the results to the values used. If the answer changes greatly with slight variations in the values of some of these parameters, this may provide the motivation and justification for expenditure of more time and money to obtain more accurate estimates. On the other hand, if the results do not change over wide fluctuations in the values of the parameter, no further effort is needed or justified.

Simulation is ideally suited for sensitivity analysis because of the experimenter's degree of control. Unlike experimentation with real world systems, the simulation modeler has absolute control over his model and can vary one parameter at a time if need be, observing the results upon the behavior of the model.

DOCUMENTATION

The last two elements that must be included in any simulation project are implementation and documentation. No simulation project can be considered successfully completed until it has been accepted, understood, and used. Management scientists' greatest failure has been in gaining acceptance and use of their labors. One of the greatests causes of failure in operations research and management sciences projects to be the user's inadequate understanding of results, and thus a lack of implementation.

Documentation is closely linked to implementa-

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tion. Careful and complete documentation of the development and operation of the model can greatly increase its useful life and chances of successful implementation. Good documentation facilitates modification and ensures that the model can be used even if the services of the original developers are no longer available. In addition, careful documentation can help the modeler to learn from his mistakes and perhaps provide a source of subprograms that can be reused in future projects.

CONCLUSIONS

The use of simulation for problem solving has become very extensive in every area of human endeavor. One would be hard pressed to name an area or field in which simulation has not been used successfully. As might be expected with such widespread use, the state-of-the-art is fairly advanced (15). However, despite the high level of activity and the rapid advances in the state-of-the-art in mathematics, statistics and computer science, simulation remains almost as much of an art as science and a tool to be used carefully. We can never be sure that our simulation model captures all of the important properties of the studied system. Simulations have the appearance of reality and can easily mislead us. Simulation in any of its applied fields is a wonderful servant but a very bad master. We must be careful that we do not mislead ourselves into confusing the model and reality.

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