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INTRODUCTION TO SIMULATION

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ABSTRACT

The purpose of this tutorial is to introduce the basic concepts of discrete simulation as a decision making aide. The advantages and disadvantages of simulation are discussed as well as the basic steps in the simulation process. Factors to be considered as well as pitfalls to avoid are presented.

1 WHAT IS SIMULATION

Simulation is one of the most powerful analysis tools available to those responsible for the design and operation of complex processes or systems. In an increasingly competitive world, simulation has become a very powerful tool for the planning, design, and control of complex systems. No longer regarded as the approach of "last resort" it is today viewed as an indispensable problem solving methodology for engineers, designers and managers.

To simulate, according to Webster's Collegiate Dictionary, is "to feign, to obtain the essence of, without the reality." Thus according to Schriber [1987], "Simulation involves the modeling of a process or system in such a way that the model mimics the response of the actual system to events that take place over time." We will define *Simulation as the process of designing a model of a real system and conducting experiments with this model for the purpose of either understanding the behavior of the system and/or evaluating various strategies for the operation of the system.* We consider simulation to include both the construction of the model and the experimental use of the model for studying a problem. Thus, we can think of simulation modeling as an experimental and applied methodology which seeks to:

* Describe the behavior of systems.

* Construct theories or hypothesis that account for the observed behavior.

* 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.

2 WHAT CAN BE SIMULATED ?

In every research study on the utility and use of operations research techniques [Shannon et al 1981, Ford et al 1987], simulation has always turned up either first or second. The reason is its great versatility, flexibility and power. When considering the question of what kinds of systems can be simulated, the answer is that almost any type has or can be studied. The broad range of applications of this methodology is almost impossible to classify. Rather than try to give an exhaustive list, we will simply try to point out some representative areas of previous applications.

COMPUTER SYSTEMS - hardware components, software systems, networks of hardware, data base structure and management, information processing, reliability of hardware and software, etc..

MANUFACTURING - material handling systems, assembly lines, automated production facilities, automated storage facilities, inventory control systems, reliability and maintenance studies, plant layout, machine design, etc..

BUSINESS - stock and commodity analysis, pricing policy, marketing strategies, acquisition studies, cash flow analysis, forecasting, transportation alternatives, manpower planning, etc..

GOVERNMENT - military weapons and their use, military tactics, population forecasting, land use, health care delivery, fire protection, police services, criminal justice, roadway design, traffic control, sanitation services, etc..

ECOLOGY AND ENVIRONMENTAL - water pollution and purification, waste control, air pollution, pest control, weather prediction, earthquake and storm analysis, mineral exploration and extraction, solar energy systems, crop production, etc..

SOCIAL AND BEHAVIORAL - food/population analysis, educational policies, organizational structure, social systems analysis, welfare systems, university administration, etc..

BIOSCIENCES - sports performance analysis, disease control, biological life cycles, biomedical studies, etc..

The above list does not even begin to cover all of the areas that have been studied using simulation. It is safe to say that one would be hard pressed to find any arena of human endeavor that has not seen some simulation activity. This list is merely intended to suggest the great utility of simulation in solving a broad range of significant problems. Simulation is a cost effective way of pre-testing proposed systems, plans, or policies before developing expensive prototypes, field tests, or actual implementations. Increasingly, management is viewing simulation as a very inexpensive insurance policy.

3 ADVANTAGES & DISADVANTAGES

The basic concept of simulation is easy to comprehend, and hence often easier to justify to management or customers than some of the analytical models. In addition, a simulation model may be more credible because it's behavior has been compared to that of the real system, or because it requires fewer simplifying assumptions and hence captures more of the true characteristics of the system.

All simulation models are so-called input-output models. That is, they yield the output of the system for a given input. Simulation models are therefore "run" rather than solved. They are incapable of generating an optimal solution on their own in the sense of analytical models; they can only serve as a tool for the analysis of the behavior of a system under conditions specified by the experimenter. The exception to this statement is that a simulation model can be used to find the optimum values for a set of control variables under a given set of inputs.

Simulation has the following benefits:

* It can be used to explore new policies, operating procedures, decision rules, organizational structures, information flows, etc. without disrupting the ongoing operations.
* New hardware designs, physical layouts, software programs, transportation systems, etc. can be tested before committing resources to their implementation.

* Hypothesis about how or why certain phenomena occur can be tested for feasibility.

* Simulation allows us to control time. Time can be easily compressed, expanded etc. allowing us to quickly look at long time horizons or to slow down a phenomena for study.

* It can allow us to gain insight into which variables are most important to performance and how these variables interact.

* Simulation allows us to identify bottlenecks in material, information and product flows.

* The knowledge gained about a system while designing a simulation study may prove to be invaluable to understanding how the system really operates as opposed to how everyone thinks it operates.

* Through simulation we can experiment with new situations about which we have limited knowledge and experience so as to prepare for what may happen. Simulation's great strength is its ability to let us explore "what if" questions.

Even though simulation has many strengths and advantages, it is not without drawbacks. Among these are:

* Model building is an art and requires specialized training. The quality of the analysis depends upon the quality of the model and skill of the modeler. Model building is an art, and as such, skill levels of practitioners vary widely.

* Simulation results are sometimes hard to interpret. Since the model is trying to capture the randomness of the real system, it is often hard to determine if an observation made during a run is due to a significant relationship in the system, or the randomness built into the model.

* Simulation analysis can be a time consuming and expensive process. An adequate analysis may not be feasible within the time and/or resources available and a "quick and dirty" estimate using analytical methods may be preferable.

4 THE SIMULATION PROCESS

The essence or purpose of simulation modeling is to provide aide to the decision maker in problem solving. Therefore, to learn to be a good simulation modeler you must learn to merge the methodologies of good problem solving techniques with those of good software engineering practise. We can identify the following steps which should be present in any simulation study:

PROBLEM DEFINITION - Clearly defining the goals of the study so that we know the purpose i.e. why are we doing it and what do we hope to find?

PROJECT PLANNING - Being sure that there are sufficient personnel, computer hardware and software resources available to do the job and that adequate management support exists.

SYSTEMS DEFINITION - Determination of the boundaries and restrictions to be used in defining the system (or process) and investigating how the system works.

CONCEPTUAL MODEL FORMULATION - Developing a preliminary model either graphically (block diagrams etc.) or in pseudo code, to define the components, descriptive variables and interactions (logic) which constitute the system.

PRELIMINARY EXPERIMENTAL DESIGN - Selection of the measures of effectiveness to be used, the factors to be varied, the levels of those factors to be investigated, i.e. what data needs to be gathered from the model, in what form and how much.

INPUT DATA PREPARATION - Identification and collection of the input data needed by the model.

MODEL TRANSLATION - Programming the model in an appropriate computer language.

VERIFICATION AND VALIDATION - Confirming that the model operates the way the analyst intended (debugging) and that the output of the model is believable and representative of the output of the real system.

FINAL EXPERIMENTAL DESIGN - Designing an experiment that will yield the desired information and determining how each of the test runs specified in the experimental design is to be executed.

EXPERIMENTATION - Execution of the simulation to generate the desired data and to perform sensitivity analysis.

ANALYSIS AND INTERPRETATION - Drawing inferences from the data generated by the simulation.

IMPLEMENTATION AND DOCUMENTATION - Putting the results to use, recording the findings as well as documenting the model and its use.

It is important that inexperienced modelers understand that the longer you wait to start step 7, the quicker you will complete both the coding and the project. Assuming of course, that you spend that time understanding the problem, designing the model and designing the experiments to be run.

Computer scientists have been devoting a great deal of effort to trying to develop design and management methods that will result in the rapid development of software while minimizing errors. These efforts fall under the heading of "Software Engineering." One of the major ideas that has come out of this effort is the validity of the "40-20-40 Rule." This rule says that forty percent of the effort and time in the project should be devoted to steps 1 through 6, twenty percent to step 7 and the remaining forty percent to steps 8 through 12 [Sheppard 1983, McKay et al 1986].

5 PROBLEM DEFINITION AND PROJECT PLANNING

It should be obvious that before you can solve a problem you have to know what the problem is. This is sometimes easier said than done. Experience indicates that beginning a simulation project properly, may well make the critical difference between success and failure.

We begin our analysis by collecting information and data adequate to provide understanding of both the problem and the system to be studied. The usual project begins with the sponsor describing the situation to the analyst in general terms and in a rather vague and imprecise way. We must consider the sponsor's problem description as a set of symptoms requiring diagnosis. The problem is usually described in terms of the sponsor's background and experience. Therefore it is often put in terms of profit and loss figures, inventory levels, delays, bottlenecks or other operational data of concern to the sponsor. The flow of events will be: diagnosis of symptoms ⇒ problem definition ⇒ model formulation.

In trying to understand and formulate the problem, we must become thoroughly familiar with all aspects of the sponsoring organization's operations relevant to the situation. This includes forces or factors outside the organization that can have an impact, and an understanding of the subjective as well as objective aspects of the problem.

An important aspect of the planning phase is to assure that certain factors which are critical to the success of the project have been considered. Some of these can be defined as:

1. Clearly defined goals - knowing the purpose of the study i.e. why are we doing it and what do we hope to find?

2. Sufficient resource allocation - being sure that there is sufficient time, personnel, computer hardware and software available to do the job.

3. Management support - insuring that management has made its support for the project known to all concerned parties.

4. Project plans and schedules - having detailed plans for carrying out the project.

5. Competent project manager and team members - assurance that the necessary skills and knowledge are available for successful completion of the project.

6. Responsiveness to the clients - care that all potential users of the results are consulted and are kept up to date as the project progresses.

7. Adequate communication channels - continuing concern that sufficient information is available on project objectives, status, changes, user or client needs, etc. to keep everyone (team members, management and clients) fully informed as the project progresses.

One of the major outcomes of the planning and orientation period will be the determination of the explicit goals or purpose of the simulation project. Simulation experiments are conducted for a wide variety of purposes, some of which are:

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

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

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

SENSITIVITY ANALYSIS - determining which of many factors are the most significant in affecting overall system performance.

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

FUNCTIONAL RELATIONS - establishing the nature of the relationships among one or more significant factors and the systems response.

BOTTLENECK ANALYSIS - discovering where the bottlenecks restricting the flow of entities through the system are located and what can be done to increase throughput.

This list is not exhaustive and merely suggests the most common goals or purposes. The explicit purpose of the model has significant implications for the whole model building 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 correspondence between the model and the real system. On the other hand, if the goal is the relative comparison of two or more systems or operating procedures, the model may be valid in a relative sense even though the absolute magnitude of responses varies widely from that which would be encountered in the real system. The whole process of designing the model, validating it, designing experiments, and drawing conclusions from the resulting experimentation must be closely tied to the specific purpose of the model. No one should build a model without having an explicit experimental goal in mind. Unfortunately, the analyst does not always understand the real world problem well enough initially to ask the right questions in advance. Thus the model should have an easily modified structure so that additional questions arising as a result of early experimentation can be answered later.

6 SYSTEM DEFINITION AND MODEL FORMULATION

The essence of the art of modeling is abstraction and simplification. We are trying to identify that small subset of characteristics or features of the system that is sufficient to serve the specific objectives of the study. Thus, after we have specified the 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 achievement of 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 outside environment. The outside environment is represented as inputs to the model.

In general, we usually have little difficulty in deciding upon the output variables. If we have done a good job in specifying the goals or purposes of the study, the required output variables are fairly obvious. The real difficulty arises in determining which input and status variables produce the effects observed and which can be manipulated to produce the effects desired.

We are also faced with conflicting objectives. We want to design 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. Experience shows that the analyst nearly always includes too much detail rather than too little. The tendency among inexperienced modelers is to try to transfer all the detailed difficulties in the real situation into the model, hoping that the computer will somehow solve their problem.

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. The definition of the model boundary is usually a tradeoff between accuracy and cost. The greater the degree of detail to be modeled, the more precise and expensive will be the input data required. Therefore, the model must include only those aspects of the system relevant to the study objectives.

One should always design the model around the questions to be answered rather than try to imitate the real system exactly. Pareto's law says that in every group or collection of entities, there exists a vital few and a trivial many. In fact eighty percent of the behavior can be explained by the action of twenty percent of the components. Nothing really significant happens unless it happens to the significant few. Our problem in designing the simulation model is to be sure that we correctly identify the vital few components and include them in our model.

Once we have decided which components and variables to tentatively include in our model, we must then determine the functional relationships among them. At this point we are trying to show the logic of the model i.e. what happens. This usually entails describing the system as a logical flow diagram using graphics or through writing pseudo-code.

7 EXPERIMENTAL DESIGN

We have defined simulation as being experimentation via a model to gain information about a real world process or system. It then follows that we must concern ourselves with the strategic planning of how to design an experiment or experiments that will yield the desired information at the lowest cost. The next step, therefore, is to design an experiment that will yield the information needed to fulfill the study's goal or purpose.

The design of experiments comes into play at two different stages of a simulation study. It first comes into play very early in the study, before the first line of code has been written and before the finalization of the design of the model. As early as possible we want to select the measure(s) of effectiveness to be used in the study, what factors we are going to vary, how many levels of each of those factors we will investigate and the number of samples we will need to run in order to carry out the entire experiment. Having this fairly detailed idea of the experimental plan early, allows the model to be better planned to provide efficient generation of the desired data.

Later on, after we have coded the model, verified it's correctness, and validated its adequacy, we will again need to consider the final strategic and tactical plans for the execution of the experiment(s). Here the project constraints on time (schedule) and costs must be updated to the current conditions and imposed upon the design. Even though careful planning and budget control may have been exercised from the beginning of the study, now is the time to take a hard , realistic look at the resources remaining and how best to utilize them. At this point we will have to adjust the experimental design to account for remaining resource availability as well as information which we have gained in the process of designing, coding, verifying and validating the model.

The design of a computer simulation experiment is essentially a plan for purchasing a quantity of information that may be acquired at varying prices depending upon the manner in which the data is obtained. The effective use of experimental resources is profoundly affected by the choice of design because:

* The design of the experiment determines in great measure the form of statistical analysis that can be used to analyze the results.

* The success of the experiment in answering the questions of the experimenter (without excessive expenditure of time and resources) also depends largely upon the right choice of design.

Simulation experiments are expensive in terms of time and labor of the experimenter as well as in some cases the cost of machine time. The primary purpose of conducting simulation studies is to learn the most about the behavior of the system for the lowest possible cost. To do so, we must plan and design carefully not only the model but also how it is to be run or used. Experimental designs are (1) economical in terms of reducing the number of experimental trails required, and (2) they provide a structure for the investigator's learning process.

8 INPUT DATA

Every simulation study involves data gathering. Stochastic systems contain one or more sources of randomness. The analyst must be concerned about data related to the inputs for the model such as the arrival rate of entities to the system, processing times required at various machines, reliability data such as the pattern of breakdowns of machines, time to repair machines, or the rejection rate of parts coming from a certain process. Data gathering is usually interpreted to mean gathering numbers, but the gathering of numbers is only one aspect of the problem. The analyst must also decide what data are needed, what data are available and whether it is pertinent, whether existing data are valid for the required purpose, and how to gather the data.

The design of a stochastic simulation model always involves the choice of whether to represent a particular aspect of the system as being probabilistic or deterministic. If the decision is probabilistic and if empirical data exists, then a decision must be made as to whether to sample directly from the empirical data or to try to fit it to a theoretical distribution and if successful, sample from the theoretical distribution. This choice is important and fundamental for several reasons. First using raw empirical data implies that all one is doing is simulating the past. The use of data from one year would replicate the performance of that year, but not necessarily tell us anything about expected future performance of the system. When sampling directly from historic data, the only events possible are those which have transpired during the period when the dat was gathered. It is one thing to assume that the basic form of the distribution will remain unchanged with time and quite another to assume that the idiosyncrasies of a particular year will always be repeated.

Second it is much easier to change certain aspects of the input if theoretical random variate generation is being used i.e. there is greater flexibility. For example, if I want to ask the question, "What happens if inputs increase by 10% per week?" I only have to increase the mean arrival rate of the theoretical distribution by the required ten percent. On the other hand, if I am sampling directly from the empirical data, it is not clear how I increase the arrival rate by the required amount.

Third, it is highly desirable to test the sensitivity of the system to changes in the parameters. For example we might want to know how much the arrival rate could increase before the system performance would deteriorate to an unacceptable degree. Again, sensitivity analysis is much easier to perform if we are using theoretical distributions instead of sampling directly from the historical empirical data.

When no historical behavioral data exists (either because the system has not yet been built or it is not possible to gather it), the problem is even more difficult. In such cases we must estimate both the distribution and the parameters based upon theoretical considerations. For guidance see Law and Kelton 1991 or Pegden et al 1990.

9 MODEL TRANSLATION

Eventually one is faced with the problem of describing or programming the model in a language acceptable to the computer to be used. Well over a hundred different simulation languages are commercially available. In addition there are literally hundreds of other, locally developed languages in use in companies and Universities. One of the issues that the analyst must face is which language to use.

It should be noted that any general algorithmic language (FORTRAN, BASIC, PASCAL, C etc.) is capable of expressing the desired model. However, selecting one of the specialized simulation languages has very distinct advantages in terms of ease, efficiency and effectiveness of use. Some of the advantages of using a specialized simulation language are:

* Reduction of the programming task.

* Provision of conceptual guidance.

* Increased flexibility when changing the model.

* Fewer programming errors.

* Automated gathering of statistics.

The ultimate goal of any programming language is to close the gap between what users conceptualize as a representation of a model and how they actually express that relationship in some executable form.

As the years have passed, new simulation languages have been developed and old ones enhanced. Language developers have focused their attention on three objectives: (1) reduced model development time, (2) improved accuracy, and (3) improved communication. There is in fact, a revolution taking place and an explosion of creative activity in simulation modeling and language development. This revolution has been brought on by developments in desktop computing, graphics and the technologies of artificial intelligence and expert systems.

The development of simulation software is currently in a transition period. The emphasis is upon ease of use and providing an integrated simulation environment rather than simply more powerful languages.

10 VERIFICATION AND VALIDATION

Once the programming of the model is functionally complete, the question should be asked, "Does it work?" Asking if a program works is in fact a two part question. First of all, does it do what the programmer expects it to do? Secondly, does it do what the user expects it to do? These two questions are answered through verification and validation. Verification seeks to show that the computer program performs as expected and intended, thus providing a correct logical representation of the model. Validation, on the other hand, establishes that the model behavior validly represents that of the real world system being simulated. Both processes involve system testing that demonstrates different aspects of program correctness.

Verification can be viewed as rigorous debugging with one eye on the code and the other eye on the model requirements. In addition to simply debugging any programming errors, the question to be asked is whether the code reflects the description found in the conceptual model. One of the goals of verification is to show that all parts of the model work independently and together using the right data at the right time.

The greatest aid to program verification is correct program design. Next in importance are clarity, style, and ease of understanding. Very often simulation models are poorly documented, especially at the coding level. Verification can be greatly helped if the analyst will comment the code liberally. There is no reason why almost every line of code should not have a comment explaining what the analyst intended for that piece of code to do.

Validation is the process of bringing to an acceptable level the user's confidence that any inference about the system derived from the simulation is correct. Basically three questions are of concern:

a) Does the model adequately represent the real world system?

b) Is the model generated behavioral data characteristic of the real system's behavioral data?

c) Does the simulation model user have confidence in the model's results?

Consequently we will be concerned with tests that fall into three groups: (a) tests of model structure; (b) tests of model behavior; and (c) tests of the policy implications of the model.

A model is constructed for a specific purpose, and it's 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 studied. Validation is a continuous process, beginning with the start of the study, continuing 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 involve in constructing the model.

Validation is a process that requires the model builder to communicate the basis 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 modeler 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 either 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 found. Validation testing goes on continuously in the process of designing, constructing and using the model.

In addition it should be remembered that verification and validation are never really finished. If the model is used for any period of time, then the data and the model itself will need to be periodically reviewed to be sure that they are still valid. Verification and validation are intertwined and go on throughout the study. They are not something that is tacked on towards the end of the study. Instead they are an integral process that starts at the beginning of the study and continues through model building and model use. It should also be pointed out, that if it is possible to involve the ultimate user in the whole simulation process, it will make validation much easier.

11 EXPERIMENTATION AND ANALYSIS

Next we come to the actual running of the experiments and the analysis of the results. In order to correctly use the computer program to generate model behavioral data through planned experimentation and analyze the results, we are faced with a set of statistical issues that are sometimes difficult to resolve. At this stage there are still numerous pitfalls awaiting the unwary. Depending upon how the experiments are conducted, we now have to deal with issues such as how long to run the model (i.e. sample sizes), what to do about starting conditions, whether the output data is correlated, and what statistical tests are valid on the data.

Since the output of a simulation model is in fact a sample of system behavioral data, all concerns regarding statistical inference from samples applies. The major concerns are that the data be representative of typical system behavior, that the sample size be large enough to provide some stated level of confidence in the performance measure estimates, and that none of the assumptions underlying the statistical calculations are violated.

In order to address these concerns, we must first ascertain whether the real system is terminating or non-terminating. Different methods are used for the running and analysis of these two different types of systems. In a terminating system the simulation ends if a specified event occurs, e.g. in a dual, one or both participants are killed or the weapons expended. In a non-terminating or continuous system, no such critical event occurs, and the system continues indefinitely, e.g. a telephone exchange. Another way to look at the situation is to consider a system terminating if the events that drive the system cease occurring at some point in time.

Terminating systems can be physically terminating (e.g. the piece of equipment fails) or it can be arbitrarily terminated by the goal of the study (e.g. determine the maximum profit for the next year). In the latter example, the terminating critical event is arbitrarily set as the end of the planning period of interest.

A second system characteristic of interest is whether the system is stationary or non-stationary. A system is stationary if the distribution of it's response variable (and hence it's mean and variance) does not change over time. With such systems we are generally concerned with finding the steady-state conditions, i.e. the value which is the limit of the response variable if the length of the simulation went to infinity without termination.

Depending upon whether the system is terminating or not and whether it is stationary or not, we must decide on how long to run the simulation model (i.e. sample size). This will first require us to decide what we will consider a single sample to be. For example, if we are considering a bank which opens each morning with no customers present and closes each day empty and idle (this would be considered a terminating, non-steady state system), a single sample could be the mean number of customers serviced per day or it could be the number serviced per week.

If the system is a non-terminating, steady state system, then we must be concerned with the starting conditions of the simulation. By this we mean, what is the status of the system at the start of the simulation run. If the system is empty and idle (i.e. no customers present), this condition is not typical of steady-state conditions. We must then either wait until the system reaches steady state before we begin collecting data or else start with more realistic conditions. This of course requires that we be able to recognize when steady state has been achieved.

Finally, most statistical tests require that the data points in the sample be independent (i.e. not correlated). Unfortunately, the data from many of our models does not meet this condition and we must do something about it before we can draw valid conclusions.

12 DOCUMENTATION AND IMPLEMENTATION

At this point we have completed all the steps for the design, programming and running of the model as well as the analysis of the results. The final two elements that must be included in any simulation project are implementation and documentation. No, simulation project can be considered successfully completed until it's results have been understood, accepted, and used. It should be obvious that this is one of the most important steps. Yet one of the major short comings of many studies is the lack of thought that goes into reporting and explaining the results of the study.

Documentation and reporting are closely linked to implementation. 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 previous mistakes and perhaps provide a source of subprograms that can be reused in future projects.

It is amazing how often modelers will spend a great deal of time trying to find the most elegant and efficient ways to model a system and then throw together a report to the sponsor or user at the last minute. If the results are not used the project was a failure. If the results are not clearly, concisely and convincingly presented, they will not be used. The presentation of the results of the study is a critical and important part of the study and must be as carefully planned and designed as any other part of the project.

Among the issues to be addressed in the documentation of the model and study are the choosing of appropriate vocabulary to fit the intended audience (no technical jargon), the length and format of any written reports (short and concise), and timeliness. We must also be sure that the reports (both oral and written) address the issues that the sponsor or user consider important [Newton and Weatherbee 1980].

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