AN INTRODUCTION TO SIMULATION MODELING

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ABSTRACT

This paper offers an introductory overview of discrete simulation, with emphasis on the simulation modeling process rather than on any specific simulation package. Examples are used to demonstrate the application of the methodology at each step of the process. An extensive list of additional readings is given for the reader who wishes to deepen his/her knowledge in a specific area.

1 SIMULATION MODELING

The word simulation means different things depending on the domain in which it is being applied. In this tutorial, simulation should be understood as the process of designing a model of a real system and conducting experiments with this model for the purpose of understanding the behavior of the system or of evaluating various strategies for the operation of the system (Shannon, 1975). In other words, simulation modeling is an *experimental* technique and *applied* methodology which seeks

✓ to describe the behavior of systems,
✓ to construct theories or hypotheses that account for the observed behavior, and
✓ to use these theories to predict future behavior or the effect produced by changes in the operational input set.

1.1 Types of Simulation

Simulation is classified based on the type of system under study. Thus, simulation can be either continuous or discrete. Our emphasis in this tutorial will be on discrete simulation. There are two approaches for discrete simulation: *event-driven* and *process driven*.

Under event driven discrete simulation, the modeler has to think in terms of the events that may change the status of the system to describe the model. The status of the systems is defined by the set of variables (measures of performance) being observed (e.g. number in queue, status of server, number of servers). On the other hand, under the process driven approach, the modeler thinks in terms of the processes that the dynamic entity will experience as it moves through the system.

1.2 Some Terminology

Every simulation model represents a *system* of some form. The system may be a manufacturing cell, an assembly line, a computer network, a service facility, or a health care facility, just to name a few. Although these systems seems to be completely different, they are not really that different if we expressed them in terms of their components. In general the components of a system are dynamic entity(ies) and resource(s).

Dynamic entities are the objects moving through the system that request one of the services provided by the system resources. Entities have *attributes* which describe a characteristic of it. Entities may experience *events* which is an instantaneous occurrence that (may) change(s) the state of the system. An *endogenous event* is an event that occurs within the system, whereas an *exogenous event* is an event that occurs outside the system.

Resources are the static entities that provide a service to an entity. Resources are further classified based on the type of service they provide; e.g. servers (machines or persons), free path transporters, guided transporters, conveyors, and so forth. Resources engage in *activities* which is a time period of specified length.

The *state* of the system is a collection of variables needed to describe the system's performance.

Simulation will model the *random* behavior of a system, over time, by utilizing an internal *simulation clock* and by sampling from a *stream of random numbers*. A *random number generator* is a computational algorithm that enables the creation of a

new number every time the function is invoked. The sequence of these numbers is known as a *random number stream*. A true *random number* cannot be generated by a computer. Computers can only generate *pseudo-random numbers*. However, these numbers are statistically random; thus, their usage in simulation modeling is valid.

1.3 The Simulation Modeling Process

The simulation modeling methodology has many stages including: definition of the project and its goals, abstraction of a model, digital representation of the model, experimenting with the model, and producing complete documentation of the project. It tends to be an iterative process in which a model is designed, a scenario defined, the experiment run, results analyzed, another scenario chosen, another experiment was run, and so forth. However, advances in computer hardware, software engineering, artificial intelligence (AI), and databases are exerting a major influence on the simulation modeling process (SMP) and the development philosophy of support tools. If we look at the SMP (Figure 1), it is clear that simulation modeling is a knowledge and data intensive process. Notice that the flow through the SMP is not a sequential one; rather, it is a highly iterative one as discussed in the following paragraphs.
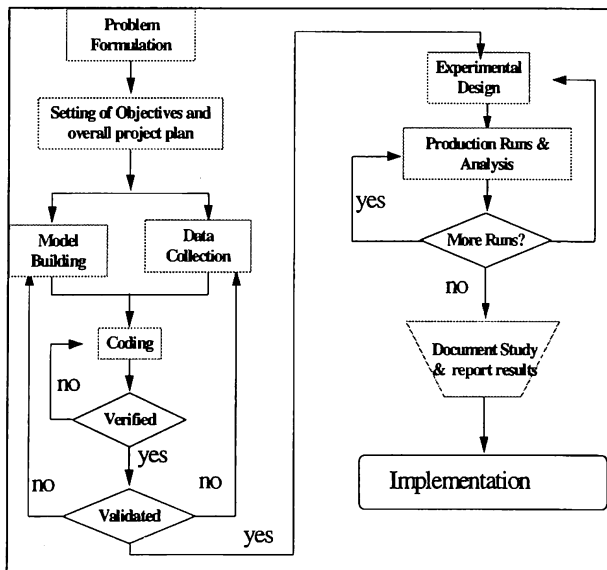

Figure 1: The Simulation Modeling Process

A study of a system starts when there is a problem with an existing system, or when it is not possible to experiment with the real system, or when the system is under design, i.e. the system does not exist yet. After

clearly understanding and assessing management needs and expectations, the modeler must determine whether or not simulation is indeed an adequate tool for the analysis of the system under scrutiny. In some instance, an analytical technique may suffice to obtain adequate solutions. Analytical tools should be preferred over simulation whenever possible. The modeler must establish a set of assumptions under which a technique, or a combination of techniques, is applicable, feasible and sufficient.

If simulation modeling is the technique, or it is part of a combination of techniques, the modeler proceeds to gather data and performs proper statistical analysis to support models of the system. The needed data may be available in many different places and/or in different formats. For example, data may reside on paper, or it may reside within a database of a computerized information system. In either case, statistical tests must be performed without altering or destroying the original raw data. When there is no data available, the modeler must define the inputs to the model about the system using rules of thumb and/or personal experience.

A conceptual model of a system must be devised and converted into a digital model. The modeler resorts to tools that will make the transition less difficult and less time consuming such as model generator front ends, simulation packages and so on. However, converting a conceptual model into a digital one is by itself meaningless, unless such a digital model is thoroughly verified and validated. The reliability of the digital model is directly affected by the quality of the verification and validation processes. *Verification* entails assuring that the digital code of the model performs as expected and intended, and *validation* seeks to show that the model behavior represents that of the real-world system being modeled.

With a reliable and accurate digital model, the modeler proceeds to the experimentation phase. Statistical experiments are designed to meet the objectives of the study. Observing a model under one set of experimental conditions usually provides little or incomplete information. Thus, a set of experimental conditions must be analyzed within the framework of multiple experimental conditions.

The capstone of the SMP is the preparation of a set of recommendations into a formal management report. This report includes implementation and operations guidelines.

1.4 Advantages/Disadvantages of Using Simulation

Simulation modeling is a highly flexible technique because its models do not require the many simplifying assumptions needed by most analytical techniques.

Furthermore, simulation tends to be easier to apply (once the programming side is overcome) than analytic methods. In addition, simulation data is usually less costly than data collected using a real system. However, despite its flexibility, simulation modeling is not the magic wand that solves all the problems. Constructing simulation models may be costly, particularly because they need to be thoroughly verified and validated. Additionally, the cost of the experiment may increase as the computational time increases. The statistical nature of simulation requires that many runs of the same model be done to achieve reliable and accurate results.

Despite its disadvantages, simulation remains a valuable tool to address a variety of engineering problems, at the design, planning, and operations levels. In each of this areas, simulation can be used to provide information for decision making, or it may actually provide a solution (Pritsker, 1992).

2 STATISTICAL ASPECTS

2.1 Statistical Tools

It is not uncommon for a new comer to the simulation modeling methodology to feel hesitant about it because of its intense use of statistics. Fortunately, there are a variety of support tools to overcome this hesitation.

Simulation packages such as SIMAN/ARENA (Banks, et al., 1994), GPSS/H (Henriksen, 1989), and SLAMSYSTEM (O'Reilly, 1994) provide some support for both the analysis of data for inputs as well as for the analysis of output. In addition, there are several packages that has been designed to support the statistical analysis needed in simulation. For example, ExpertFit (Law and Vincent, 1995) enables the input data modeling for up to twenty seven probabilistic models; a variety of statistical tests and measures of accuracy are implemented in this package. Another example is SIMSTAT (Blaisdell and Haddock, 1993) which is an interactive program that allows the analysis of both input and output data. Both packages are Windows-Based, and they both allow for the user to save their outputs in various formats.

In the following paragraphs, a discussion of some of the issues and techniques needed are discussed.

2.2 Analysis of Inputs

A simulation model requires data and/or data models for to come alive. Without input data models, the simulation model itself is incapable of generating any data about the behavior of the system it represents. A simulation practitioner may be confronted with one of

three possible scenarios at this stage of the SMP:

☑ *There seems to be an immense amount of data*
☑ *There is no data at all*
☑ *There is a few amount of data*

On the onset, the first situation may appear to be ideal: the more data, the merrier. But, caution must be exercise as the data available may be irrelevant for the purposes of the study. Even if the data presents itself as relevant to the study, traditional common sense practices must be done before using the data to develop models for simulation. Is the data reliable? How was it collected? Are there any circumstances that occurred during the data collection process that may lead to skewed or bias data models? Once sufficient information about the data and the data collection process has been compiled, classical statistical techniques should be used to develop data models. Some of these techniques are correlation analysis, point and interval estimation, linear and non-linear regression, and curve fitting in general.

Assume that there is a sample in the available data set that represent the number of customers that arrived at a bank in a 15-minute time interval.. Further, assume that these data was collected over the course of two weeks, between the hours of 9:00 AM to 2:00 PM and 5:00 PM to 6:00 PM. Correlation analysis will help answer questions such as *is the customer arrival rate constant through the day? throughout the week? If it is not, how does it vary? Could the arrival rate be modeled differently for each type of service the bank provide? If yes, do the data lend themselves for proper breakdown?* The use of graphical techniques such as line graphs and scatter plots will also help in establishing how to cluster the data set. Figure, for instance, reveals that there are changes in the rate of arrival throughout the day. Further, it seems that there is a variation of the rate of arrival depending not only on the time, but also on the day of the week. Correlation analysis should be used to confirm the visual hypothesis.
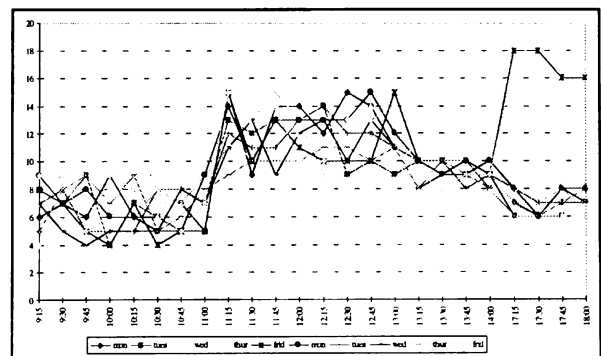

Figure 2: Line Graph of Sample Data Set

It is important that these previous questions be answer by analyzing the data because if it is assume that the entire sample of 1000 observations comes from the same *population*, a single data model may be built for it which will not reflect the true arrival rate behavior.

In our example, it is possible to construct three different probability data models to account for the change in the arrival rate. Goodness of fit tests, such as the χ^2 test and the Kolmogorov-Smirnov test need to be done to test the hypothesized distribution. In our example, we could formulate that

H_0 = *arrival rate follows a uniform distribution between 9:00 AM and 11:00 AM*

After using point estimators for the lower and the upper bounds of the uniform distribution, we can test H_0 using the χ^2 test if the number of observations is adequate and if the expected number of observations in each and every interval is at least five.

The second situation is clearly the worst case scenario because the simulation practitioner has to rely on his/her experience and knowledge about the system to establish appropriate input data models. In this case, the modeler has to quantify his/her educated guesses based on any estimated values available. Such estimates may come from the people who operate the system. In some cases the estimates given by the operators may just be an "average" or mean value. Depending on the actual system, the modeler may use such value as a constant or as the mean value of a distribution. To decide on the distribution, the modeler should use knowledge about the areas of application of the distributions. Table 1 give a summary of some classical distributions and what they are capable of modeling.

The third situation requires some of the efforts of the first one (assessing quality of data, data collection process and so forth). Usually, there is a small sample from which one has to develop data input models. Statistical methods based on the *t*-student distribution are utilized. If the sample size is "large enough", then techniques based on the Normal distribution may be used.

2.3 Analysis of Outputs

The actual analysis of the data provided by the simulation model will depend on the initial objectives of the study and on the type of system being modeled (Sadowski, 1993). There are two basic types of systems: terminating and non-terminating.

Distribution Name:	*Binomial*	*Poisson*
Definition of Variable:	X = Number of successes among n Bernoulli trials	X = Number of events during *one unit* of measure (time, volume, length,..)
Some Assumptions:	It can be used in cases where experiment consists of a sequence of n trials and n is fixed. Trials are dichotomous & identical (Bernoulli trials). Trials are independent and have same probability of success. Commonly used to model quality control and reliability data models.	Binomial converges to a Poisson (n $\rightarrow \infty$ and $\pi \rightarrow 0$). It provides probabilities of how many events will occur over a period of time. Events occur at some average rate. Rate of events remains constant over the duration of a unit of time. No two events can occur simultaneously. Commonly used in queueing analysis and to model rate of arrivals / rate of service.
Distribution Name:	*Normal*	*Exponential*
Definition of Variable:	X = *depends on the system under study*	X = time or distance between two consecutive events
Some Assumptions:	It can be applied to model physical, chemical properties. It is the best know and most widely used distribution. It can be used to model both discrete and continuous variables, but with caution because its domain is real and expands from $-\infty$ to $+\infty$	It is a special case of the Gamma model (r=1). It is *memory-less* when modeling time In a Poisson process, the rate of arrival / service is Poisson and the time between arrivals / services is Exponential.

Table 1: Summary of Some Distributions

Terminating systems are systems that have a clear point in time when they *start* operations and a clear point in time when the *end* operations. For these type of systems, it is required to established the sample size and the simulation length. The latter is usually established by the context of the problem. For a bank facility, it may be the entire day, or just the rush hours during Friday afternoon. The sample size is established, based on the accuracy, reliability, and variation desired for the study, using the equation

$$n = \frac{z_{\alpha/2}^2 \sigma^2}{d^2}$$

where *d* is the accuracy expressed in the same units as those of the measure of performance (e.g. within 5 minutes), *z* is the critical value from the standard normal table at a given reliability level, 1-α, (e.g. 95% reliability leads to an α = 0.05), and σ is the standard deviation desired.

The value of *n* is the minimum number of *replications* (not runs) needed to have statistically valid results. It is very common for the novice to confuse a replication worth a simulation run. A run is what happens from the moment the user clicks on the run option of the main menu, to the moment in which the software finishes outputting data and comes back to the main menu. A replication, on the other hand, is what happens from the simulated *start* time to the *closing* simulation time. A simulation run of this type of systems has *n* replications. The summary report from replication to replication is different, but the summary reports from run to run are exactly the same, unless the random number stream is changed between runs.

Non terminating systems are systems that have no clear beginning time when they start operations, nor do they have a clear point in time when they stop operations. For this kind of systems, it is necessary first to bring the simulation model to steady state before the model generated data is used in analysis. All the data generated before the model reaches steady state should be thrown away. Upon reaching steady state, it is necessary to decide the length of the single replication that is to be run. Usually, the method of batching is used to analyze this data. Batching refers to the breaking the highly correlated, sequential observations generated by the model, into groups or batches. These batches would then be treated in the same fashion as the replication in the case of terminating systems.

A batch is formed based on the level of correlation between observations separated by a given lag *k*. Statistical theory tells us that the farther apart two

correlated observations are, the smaller the correlation. So what one needs to do is to compute the correlation factor for various values of the lag *k* (20-500), graph the correlation factor, and identify the lag value at which the correlation actor ρ is approximately 0. From that process, the number of observations in the batch is established taking into account that this is a random process, so a safety factor needs to be added.

Once the batches are formed, each batch is treated as an independent replication, and similar analysis to that for a terminating system should be done. Regardless of the type of system, the modeler must keep in mind that reporting point estimates of the measure of performance are not that helpful. Confidence intervals on critical measures of performance should be built to add credibility and robustness to the study.

3 CODING THE MODEL

This the stage that, at first, seems to be the most time consuming. However, without proper planning and proper analysis, the effort at this stage is useless. It does not matter how "beautiful" the model looks like (animation), or how fancy (full of details) the model is. If it does not addressed the original problem, it is useless.

The modeler must be knowledgeable about programming and/or a simulation package. Although simulation models can be built using general purpose languages such as C/C++ and FORTRAN, nowadays there are a significant number of packages that have proven themselves as versatile and robust. Some of these packages are domain specific, while other are more general purpose. These packages include GPSS/H™, GPSS/World™, SIMAN/ARENA®, SLAMSYSTEM®, WITNESS, SIMFACTORY, ProModel, AutoMod, AIM, and Taylor (Banks, 1995).

4 VERIFICATION & VALIDATION

Verification is the process of determining that the model operates as *intended*. In other words, it is the process of debugging the model. All the verification activities are closely related to the model. An empirical way to check if the model is behaving as the modeler intended is to put constant values for all the random processes in the model, and to calculate the outputs the model is supposed to give. This process is by no means sufficient or enough to declare a model as verified, but it helps to identify subtle errors. In fact, determining that a model is **absolutely** verified may be impossible to attain.

During the verification stage, the modeler must test

each major component of the model. These can be done by doing *static* testing (correctness proofs, structured walk through) or by doing *dynamic* testing (execute the model under various conditions) (Sargent, 1984 and 1994)

Validation is the process of ascertaining that a model is an acceptable representation of the "real world" system. The validation process is concerned with establishing the confidence that the end user will have on the model. Some critical questions to ask during this stage are *does the model adequately represents the relationships of the "real" system?, is the model generated output "typical" of the real system?*. Validation requires that the model be tested for reasonableness (continuity, consistency, and degeneracy). A point to start the validation process empirically is to question the structural assumptions of the model as well as the data assumptions made early in the SMP. A more sophisticated way to validate a model may require the use of some analytical tools such as Queueing Theory, but for it additional data may be needed (Sargent, 1994).

In summary, verification and validation can be informal (audits, face validations, Turing test, walk through), Static (consistency checking, data flow analysis), Dynamic (Black-box testing, regression testing), Symbolic (cause-effect diagrams, path analysis), Constraint (assertion checking, inductive assertions), and Formal (Logical deduction, Predicate calculus, proof of correctness). For more details in any of these test, see Balci (1995 and 1996).

5 ENSURING SUCCESS

Simulation modeling is very susceptible to the ability of the project to leader to organize the study. It is paramount to clearly define the objectives of the study; otherwise, there will be no clear guidelines as to what type of experimentation should be done. Further, establishing which assumptions are acceptable depends on what the objectives are.

A modeling strategy needs to be developed early in the process. The complexity of the system may be too much to include in the model. In fact, such level of complexity may not be desirable. A model can be simplified by *omission, aggregation,* or *substitution*. Omission refers to leaving out details that are negligible; for example, sojourn time over a two-foot distance by human being. Aggregation refers to the lumping of details / activities; for example, it may not be possible to model the time it takes to move a box from one table to another, when the tables are next to each other, but it may be possible to measure the time it takes from the moment the server seizes the box,

opens it, performs whatever activity is supposed to perform, and places it on a cart. Substitution refers to replacing an object in the system for another one with similar, not equal, characteristics; for example, assuming that two cashiers at a fast food place work at the same speed, when indeed they do not.

It is very typical for novice simulation practitioners to resist omission. They want to build an "exact" replica of the real world system. This situation may lead to costly and delayed simulation studies. Similarly, a very experienced modeler may fall I in the trap of simplifying a bit too much. The impact of the simplifications made on the model generated data must be taken into consideration before implementing the simplifications. Again, the impacts are assessed in light of the objectives of the study.

It is very important that the modeler, or someone in the team, be properly trained in both simulation modeling and statistical analysis. A common pitfall of simulation studies is poor analysis of both the input data (to formulate data models) and the model generated data.

A simulation study is not a simple task. Instead of setting an absolute delivery date, plan on having intermediate progress reports. This approach will help you and the end user of the model to verify, validate and accept the recommendations of the study. It is very likely that as you make a progress report, the owner of the system points out that you have not quite understood a portion of the operations of the system.

In summary, keep in mind the maxims outlined by Musselman (1994), and transcribed below:
✓ Define the problem to be studied, including a written statement of the problem-solving objective
✓ Work on the right problem; fuzzy objectives lead to unclear success.
✓ Listen to the customer; do not look for a solution without firsts listening to the problem.
✓ Communicate; keep people informed, for the journey is more valuable than the solution.
✓ Only by knowing where you started can you judge how far you have come.
✓ Direct the model; advance the model by formulating it backwards.
✓ Manage expectations; it is easier to correct an expectation now, than to change a belief later.
✓ Do not take data for granted.
✓ Focus on the problem more than the model.
✓ Add complexity; do not start with it.
✓ Do not let the model become so sophisticated that it compensates for a bad design, or so complex that it goes beyond your ability to implement.
✓ Verbal agreements are not worth the paper they are printed on.

✓ Customer perceptions require attention.
✓ Report successes early and often.
✓ If it does not make sense, check it out.
✓ People decide; models do not.
✓ Know when to stop; ultimate truth is not affordable.
✓ Present a choice; people do not resist their own discoveries.
✓ Document, Document, Document!

6 CONCLUDING REMARKS

This tutorial has been intended as an introduction to this powerful technique. In-depth study of other sources is strongly recommended before engaging in a simulation study. Sources for simulation modeling include Nelson (1995), Banks and Carson (1984), Law and Kelton (1991), Sadowski (1993), Pidd 91994). For statistical analysis, recommended source include Nelson (1992), Law and Kelton (1991), and Alexopoulos (1995). For software selection, Banks (1995) is a good starting point. For the methodology in general, excellent sources include Pegden, Shannon, and Sadowski 1995), Shannon (1975), Banks and Carson (1991), and Law and Kelton (1991).

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