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Why Simulation?

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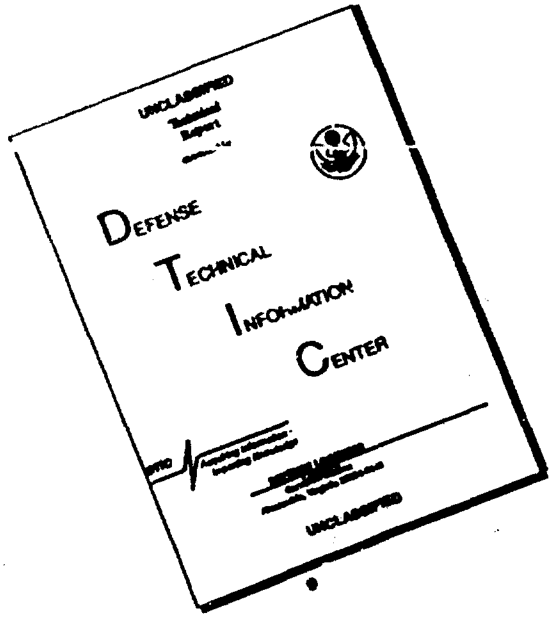

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Why Simulation?

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FOREWORD

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Why Simulation?

INTRODUCTION

Only a short time ago it was quite difficult to obtain funds for a simulation project outside certain areas of very specialized research. Practical managers who really expected useful answers to questions concerning operating problems were rarely interested in investing money in simulation. In the past 2 years this reluctance seems to have diminished considerably. Simulation is now looked on in many areas as a practicable means to obtain answers to questions raised by managers running a business, operating a government agency, or conducting a military operation. Simulation has joined the growing number of "OK words" used in our profession. Simulation is "in" along with management-information systems, real time, and timesharing.

In many respects we should be delighted with this turn of events. Simulation is generally a great deal of fun. It is very much like being given a giant erector set with which one can build the most elegant and esoteric toys ever. Most desirable of all—simulation is considered to be a form of research, and therefore the practitioner is seldom faced with embarrassing questions about the real value of his expensive project. With any luck at all the simulation-project manager can so dazzle the customer with tales of the elegance of the simulation language and complexity of the model that he may never be asked if any useful product has been obtained.

Of course there have been many useful and productive simulation projects. Fortunately, these successes have occurred with a high enough frequency to maintain our faith in the value of the technique. My concern is that there seem to be altogether too many simulation models being built that are unlikely to produce any useful results. More dangerous still, there seem to be many simulation models that produce apparently useful, but unverifiable answers. They must be either ignored or accepted on faith.

From a professional point of view, I am concerned that we are overselling simulation as a technique. From a practical point of view, I am concerned that the pendulum may well swing back in the next 2 years to the point where simulation is regarded as an untrustworthy and expensive form of boondoggle. Simulation is an extremely valuable tool when used properly to attack problems amenable to simulation, but a most wasteful and inappropriate tool when other techniques are available.

Now that people have lost their skepticism, the next problem is to develop our own restraints if we are to avoid wasteful and misleading simulation projects.

DEVELOPMENT OF SIMULATION

If the limitations of a simulation are to be discussed, first we must define simulation. The literature in the field is of limited usefulness in defining the term exactly. The more recent the document, the more likely it is that the author will quote several alternative definitions, reject them all, and proceed to develop his own, which is more general and less restricting than any of those given (see Naylor et al[1]). The use of the term "simulation" seems to outgrow even the broadest definition. I will not attempt a precise definition but as an alternative will suggest that the history of the development of simulation as it is known today may be a less rigorous but more satisfying way to describe simulation.

The origins of simulation are generally traced to the work of von Neuman and Ulman in the late 1940's. They coined the term "Monte Carlo analysis," to describe a technique whereby essentially deterministic problems too expensive or too complex to solve analytically could be solved by treating them as stochastic problems. The genius of their method was that it was an inversion of the usual approach to stochastic problems—that of treating stochastic problems as if they were deterministic, in order to solve them analytically. The Monte Carlo approach was, then, the process of finding a stochastic analog to the deterministic problem in order to estimate the solution through simulation.

Figure 1 is a greatly simplified example of Monte Carlo analysis. The area enclosed by the outline of the glass could be calculated through integration of the function that represents the sides of the glass, but such integration might be difficult and costly. The Monte Carlo approach would be to enclose the cross section of the glass by a rectangle of known area. An appropriate sample of randomly generated points is then plotted in such a way that all points within the rectangle have an equal chance of being selected. The area within the glass is then estimated by multiplying the fraction of all points that fall within the glass by the area of the rectangle. This example is a relatively simple two-dimensional case; however, the basic technique can be applied to problems of significantly greater complexity that may not be solvable by analytical means.

The development of Monte Carlo analysis occurred concurrently with the development of the high-speed computer, and as a result most applications were soon being conducted with the use of a computer. The techniques so developed were then applied to problems that were basically stochastic. Then followed a rapid application of the technique to many of the classic stochastic problems not amenable to analytic solution, e.g., processes involving multiple-channel queues. A great deal is known about scheduling and relating problems as a result of the availability of these techniques and the digital computer. In the process a body of knowledge concerning the computer modeling of real-world processes was developed that has become the real basis of computer simulation as it is known today.

Figure 2 indicates a simple example of the stochastic simulation of a stochastic process. Here the problem is the interaction of the arrival of orders and the service time of each of the processes that lead to queues forming ahead of some processes and a particular distribution of total order-processing time. Here the rate of arrival of new orders is known, as is the distribution of service

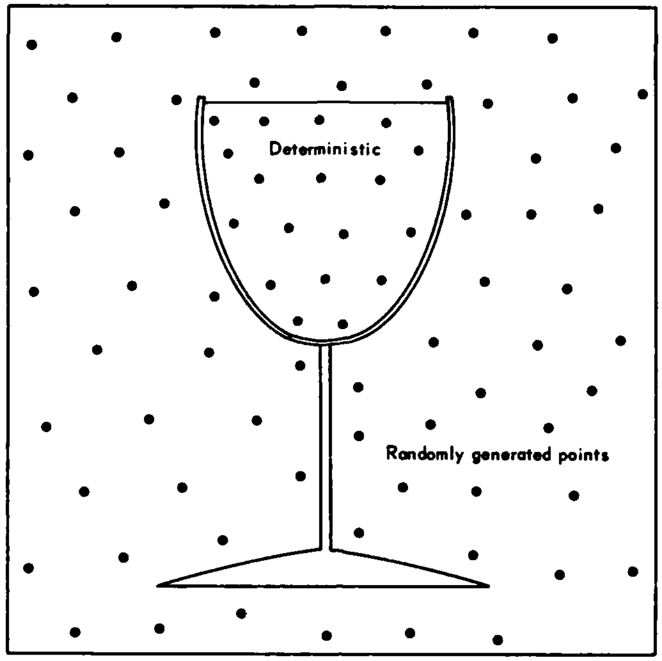

Fig. 1—Monte Carlo Stochastic Approximation of a Deterministic Value

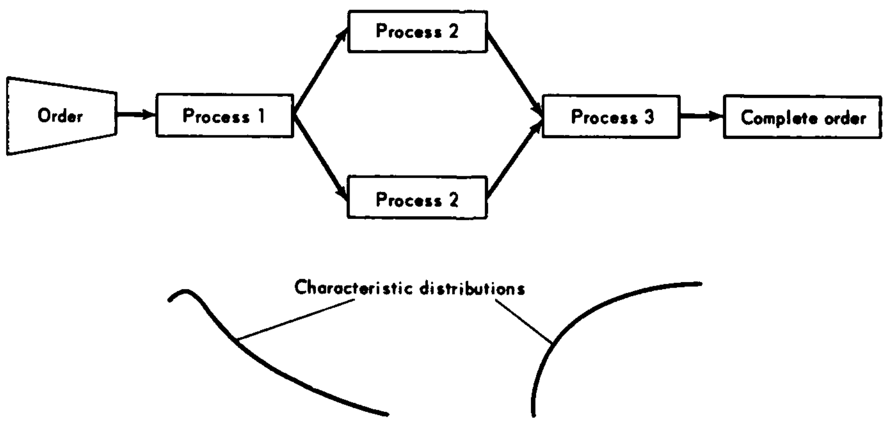

Fig. 2—Stochastic Simulation of a Stochastic Process

tim s for each of the processes. The basic simulation approach is to generate arrivals and service times by selecting from the known distributions of the times through the use of random numbers. Thus the whole procedure can be described as the development of a distribution for the total process, based on detailed knowledge of the behavior of each of the components.

A key point not always recognized is that the simulation of large queueing systems began after a well-developed theory of the behavior of the single-channel queue was available. Large simulation models of queueing systems were then constructed using components that were understood. The success of this general type of model has led some to attempt the modeling of large systems in which little is known of the behavior of the individual components.

A somewhat later development was the use of computer modeling techniques to study business, economic, and organizational problems. Clearly these processes are probabilistic in nature and not deterministic. Yet some of the foremost practitioners chose to develop deterministic models of these systems. For example, Jay Forrester's industrial dynamics[2] approach is essentially deterministic. Forrester chose to study the dynamic character of industrial systems first without the noise created by random events; only later did he introduce stochastic elements to observe their effect. This approach is prompted by the belief that the probability functions of such processes are not yet known in sufficient detail to support a useful stochastic model and further that there is much to be learned about the dynamic properties of these processes aside from their probabilistic elements. Thus an essentially deterministic approach is used to study a probabilistic process.

Figure 3 is a simple example of the deterministic approach such as might be used in an industrial dynamics simulation. Here the focus is on the feedback

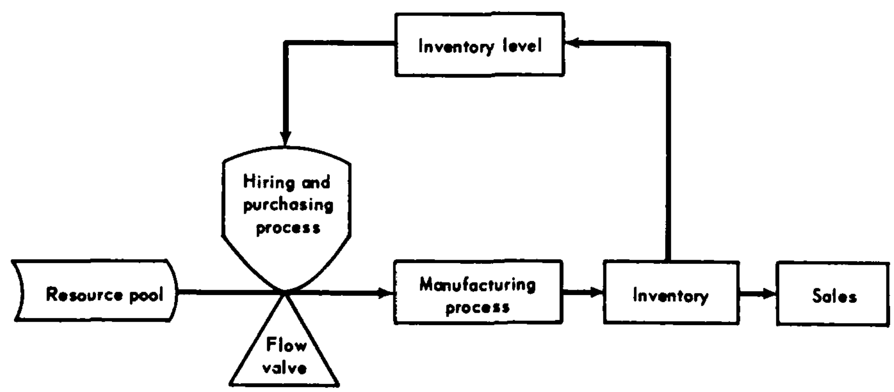

Fig. 3—The Deterministic Simulation of a Stochastic Process

problem of control. The controlling manager observes the level of inventories and, acting on this information, regulates the flow of resources into the manufacturing process. The emphasis here is on the oscillations of the system that may be created by the information and control mechanism.

Although this review has certainly not defined simulation in any rigorous way, simulation models can now be characterized in two ways: first by describing what they are not. Simulation models do not purport to find the best solution to any problem; they are not optimizing in any sense. The best to be said about any simulation model is that it describes the object process, using characteristics that are important to the results the model builder wishes to study. A simulation model thus serves its function by demonstrating the consequences of a particular set of inputs and decision rules applied to the process. The model builder is free to change any of these in the hope of improving the result, but improvement is by no means guaranteed. Thus, if optimization or improvement is the model builder's goal, that improvement must be obtained through inference from the model's behavior.

Second, we can say what simulation is like. Simulation has many of the characteristics of a laboratory experiment; it certainly can be controlled. Any run of any simulation can be replicated precisely, or any element changed to exactly the degree wished. Since the digital computer is a deterministic mechanism, the conditions of the simulation can actually be controlled to run more accurately than the conditions of the laboratory model.[3]

Simulation, like laboratory experiment, is also an abstraction from the real world. Laboratory experiments seem at first to have an advantage in that we usually separate some material, an actual part of the real world, and place it in the controlled conditions of the laboratory. One is tempted, therefore, to think that the laboratory experimenter has no problems in proving the validity of the abstraction, but clearly this is not the case. The laboratory experimenter must be concerned that in his abstraction the basic condition he wishes to study has not been altered. He must be concerned that he is faithfully reproducing in the laboratory the conditions that are important to the process he wishes to explore. This, of course, is precisely the problem that the simulation-model builder must consider.

If simulation is in effect an experimental process, a number of things can be inferred from the experience gained in the laboratory experiment. One is that laboratory procedure is carefully followed and reported in such experiments. The simulation analog of this may be the strict control and reporting of the random-number generators used, the collection and tabulation techniques used in gathering the basic data, the sample sizes used, and other related techniques.

An important point here is that in simulation there is not yet a formalized set of control techniques that ensures the accuracy of simulation experiments. The skill, experience, and thoroughness of the individual experimenter are all-important. There is no cookbook formula that permits the nonparticipant to assure himself that the results of a simulation experiment are valid.

Another similarity between a simulation and laboratory experiment is the results that one can reasonably expect. The simulation-model builder hopes that he will be surprised by the results of his model. He hopes that the model will behave in a manner that he would not have predicted and yet not violate any of the known characteristics or relations of the object system. For, if surprising results occur, the model builder may have discovered some new and interesting property of the object system not apparent before.

Of course, many surprises turn out to be the result of a failure in the model rather than a legitimate key to new understanding. The separation of surprises into these two categories is one of the most difficult problems of simulation.

A second result that one can hope for from simulation and experimentation is that the relative merit of two or more courses of action can be tested. Acknowledging the imperfections of the models, one may still hope that they will be capable of distinguishing a better set of decision rules or a more favorable set of inputs. This implies the measurement of the result against the changes to the model or its inputs. Consequently the measurement of results is as vital in simulation as it is in physical experimentation.

ADVANTAGES OF SIMULATION

The limitations as well as the advantages of simulation are perhaps most succinctly stated by Teichroew and Lubin[4] as the following:

> Simulation problems are characterized by being mathematically intractable and having resisted solution by analytic methods. The problems usually involve many variables, many parameters, functions which are not well behaved mathematically and random variables. Thus, simulation is a technique of last resort. Yet, much effort is now devoted to 'computer simulation' because it is a technique that gives answers in spite of its difficulties, costs and time required.

One advantage of simulation then is that problems not otherwise feasibly solved are open to investigation. I would submit that this is the only true advantage. In all other respects—cost, elapsed time required for solution, skill required of the analyst, and accuracy of the results—simulation is second best if a reasonably realistic analytic solution is available.

There are, of course, cases where analytic or experimental solution is theoretically possible but practically difficult or infeasible. In the vast majority of cases, however, if an analytic solution is available it should by all means be used. The point here is that simulation's single overwhelming advantage is that it is often the only feasible approach to important problems.

This idea is not always popular with people in the simulation field. Other additional advantages are often cited. One of the proposed advantages is that simulation permits more complex, more elegant, and hence more realistic models. This is certainly true. The number of variables and parameters may in some cases be larger (by an order of magnitude) than currently available optimizing models. Types of functions not feasible in analytic models can be used relatively easily in simulation models. The richness and variety of the modeling language available to simulation is certainly greater by far than in available optimizing models.

The real question is, "Does the complexity pay off?" Elegance for its own sake is not very valuable. Complexity pays off only if it truly adds to the realism of the model and if that realism is necessary to a useful solution. Thus complexity is not an advantage per se, but only if it is the sole recognizable path to solution.

Another advantage sometimes cited is that simulation can be used even in the cases where the process is not fully understood and/or the data are not complete. This too is quite true. If one is willing to make the necessary assumptions, a simulation model can be developed for virtually anything that can be conceived. In some cases the construction of a simulation model may be excellent preparation for the gathering of additional data. The process of building and exercising a simulation model has a remarkable way of focusing one's attention on the need for specific data, and the necessity for better understanding of particular aspects of the object process. But then isn't this a claim that can be made for all model building?

There is much to be said for an approach to problem solving that uses simulation to test the consequences of data and hypotheses already at hand and to focus on the areas in which additional work needs to be done. Two things must be said of this approach: First, other modeling methods can make the same claim; hence, if simulation is chosen, it should be because no simpler or cheaper approach may be used. Second, there is great danger in this approach in that the first answers are all too often taken as <u>the</u> answers. Thus simulation in the face of poor data and weak theoretical foundation is an advantage only if the weakness of the outputs as well as of the inputs is recognized. Simulation is not a machine that converts weak inputs and assumptions to strong results and conclusions.

Finally, it is sometimes stated that one of the advantages of simulation is that the manager himself can understand simulation models without the intensive training or technical background generally thought necessary for the use of optimizing models. This conclusion is subject to considerable argument. First, let us recognize that those citing this as an advantage are generally talking about operating problems and nontechnical managers. It is true that one can generally explain the basic approach to simulation to nontechnical managers more readily than one can explain, e.g., linear programming. Further, the outputs of simulation are frequently easier to understand because they are themselves simulations of object-system reports. If this advantage is restated to read, "The results of simulation models are easier to sell because they can produce results similar to those produced by the object system," then I think we must admit this is true.

Simulation can be described as the computerization of experience. That is, in the study of operating processes we build our model based on the practical knowledge of the object process and then, by running it repeatedly, gain "years" of experience in a relatively short time. Thus, although the manager may not understand the intricacies of stochastic processes, he can appreciate the basic trial-and-error approach.

It seems to me that this advantage is also a danger. Simulation models, no matter how thin the data or how limited the understanding of the object processes, can almost always come up with answers. If the answers are superficially understood, a source of misinformation may be created. I would therefore suggest that this advantage is also a trap. It might be better if the results of simulation could not be understood without extensive training and in-depth understanding.

MODELING PROBLEMS AND SIMULATION

It is not always popular to refer to the problems that are encountered in any endeavor. We prefer to discuss interesting situations or challenges.

In simulation there are a number of interesting situations that one should recognize before plunging into the world of simulation modeling.

One of the first to be recognized is the fact that good simulation requires skilled and experienced analysts. The analyst's first and perhaps most important job is to select the properties of the object system that are important to the process being studied. This implies deep understanding of the process itself, and considerable skill in modeling. The model builder thus needs thorough familiarity with the object process, skill in working with the modeling language, and skill in exercising the model.

Few simulation models are constructed in this fashion. Their functions are more commonly separated. One individual or group examines the object process and determines the properties that are important; a second individual or group then maps these properties using the simulation language. In many cases a third individual or group then conducts experiments with the model and interprets the results. There would seem to be no necessity for having a single person perform these tasks; however, there is certainly a clear need for superior communication to ensure that the modeling process or the experiments do not go beyond the capability of the conceptual model.

A second requirement is thorough technical knowledge of the statistical processes involved. Experiments with simulation models should be as carefully controlled as any physical experiment. The achievement of the steady state by the model, measurement of the behavior of the model, and selection of the sample size to be used are all tasks that require considerable technical capacity beyond that which is normally considered necessary for programming.

Finally, considerable skill in planning experiments and interpreting their results is needed. In its present state of development, simulation is an art, not a science. Experience and intuitive skill play a very important part in differentiating between genuine new information of the object process and the anomalies of the model itself.

A fundamental problem affecting all models, but particularly simulation models, is the difficulty of determining the model's validity. This problem has not been solved in any rigorous sense and may never be solved rigorously. One aspect of the problem is illustrated by the following two statements:

(a) Simulation models are valuable because they permit observation of processes otherwise difficult or impossible to observe in the real world.

(b) Simulation models are valid if they behave as the object system behaves.

These statements are of course simplified and perhaps imprecise but they do summarize valid points. A model, by definition, will not behave in all respects as the object system behaves. One of the important characteristics of a model is that it permits concentration on the parts of the object process that are believed to be important. Yet ultimately the findings that are most important to us are not directly observable in the object system. One can always deflate a simulation-model builder by classifying all his results in two categories, (a) those results obtained by observing the system directly and (b) those results that are unsupported.

The validity problem is summarized in Fig. 4. A is the object system, and B is that portion of the object system directly observable, such that B is a subset of A.* C is then the model. Now the model by definition does not contain all the characteristics of the real system. Thus AC' and ABC' are not empty. In addition, $A'C$ will not be empty, i.e., the model will contain anomalies that are characteristic of the model and not of the object system. $AB'C$ is valuable information. These are the characteristics of the model

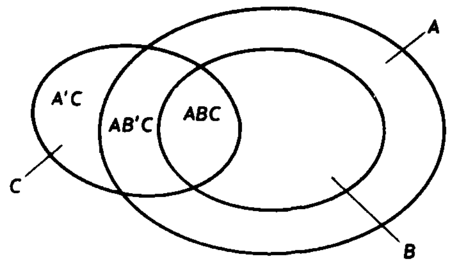

Fig. 4—The Object System Validity Problem

A = object system
B = observable portion of the object system
$B \subseteq A$
C = model
$A'C$ = anomaly of the model
$AB'C$ = valuable information
ABC = validity confirmation space

and of the object system that are not observable. ABC is the validity confirmation space. That is, it is in this region that the validity of the model may be tested by comparing its performance with the observed performance of the object system.

Now the above discussion is a conceptual one, but it illustrates the fundamental problem of simulation; i.e., as each experiment is conducted on the model the results may be classified into two categories. One category consists of the region ABC, which contains the points in which the observable portion of the object system and the model coincide. This is the region on which our claims for the validity of the model is based.

The second classification consists of the union of $A'C$ and $AB'C$ ($A'C \cup AB'C$). That is, the results may consist of invalid and/or valid results of the model. Herein lies the crux of the validity problem. The valid and invalid results cannot be distinguished without resorting to information outside the simulation process.

The usual defense against attacks on the validity of one's model is to point to the great detail and precision of the model itself. It is implied that greater detail and complexity ensures greater realism and, it is hoped, greater validity. In short, simulation-model builders frequently find themselves driven to larger and larger models of unfathomable complexity. One gets the impression that the prize goes to the most complex model rather than the one with the most useful results.

*B will not be a subset of A unless our observations of the system are completely accurate. $A'B$ is in fact the region of inaccurate observations.

This complexity leads to some curious situations. It is not uncommon to discover that a simulation model of a sequential process is made up of components that vary widely in their levels of detail. One component may be built in the greatest detail with all the elegance and complexity that its builder can devise; its outputs, however, may be digested by the next component in such a manner as to lose the detail generated in the previous step.

Model complexity is in itself a problem. It is the unexpected result that is most desired in model building and experimentation. When that unexpected result is found, however, a reasonable explanation is normally sought, i.e., an attempt is made to explain the outcome as the result of known properties of the object system. The complexity of models works against us in this situation. It is found sometimes that our model is so complex that we are unable to trace the outcome to the originating causes within the object system. When this situation occurs, the model builder has a difficult choice. He must redesign the model, search elsewhere for confirmation, or plunge into conclusions knowing they may be based on characteristics in the model but not in the object system.

In our earlier definition of simulation, we characterized simulation as nonoptimizing. It hardly seems fair now to state this as a limitation. I would submit, however, that this characteristic of simulation is an operational limitation as well as a theoretical limitation.

In actual practice we really do not expect to optimize real-world processes as a result of "optimizing" models. Such models tend to oversimplify the real world, and they can rarely be put directly into practice. Optimization is an elusive goal; it is extremely difficult if not impossible to formulate our true objectives in precise form, let alone solve for them.

Optimizing models do, however, have one great operational advantage: we know when the stated objective has been accomplished. This is not to say that the model cannot be reformulated or the objective function altered; but, given the model and its objective function, experimentation does end.

Simulation models have no such built-in assurances. It may be possible to identify improvements, but one can never be assured that some small change will not result in a major improvement. Progress is being made in the development of techniques for the systematic exploration of simulation models, e.g., SimOptimization.[5] However, currently, a systematic means to locate improvements is still unfound.

CONCLUSIONS

Simulation is a powerful technique that has been used in the past and will be used in the future to solve important problems. Simulation is, however, not a cure-all or a panacea. It is a technique of last resort. A perfectly valid goal of simulation may be the organization of ideas and knowledge of a problem to the point where other techniques may be applied.

It is not uncommon for simulation-model builders to discover that they can predict the results of runs using their models with relatively simple analytical procedures.

If this is true, then simulation analysts should study optimizing techniques thoroughly, both to avoid attempting simulation of analytically solvable problems and to direct their thinking toward the kinds of solutions that may be most useful and productive.

It is concluded that simulation models should not attempt too much in one leap. If massive breakthroughs are attempted in one step, the results will likely be unverifiable. We may be unable to distinguish the results that are truly new information about the object process from those that are aberrations of the model.

Finally, we, as computer professionals and those to whom simulation problems ultimately come, should be most careful in explaining to the customer what he may reasonably expect from simulation.

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