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INTRODUCTION TO SIMULATION IN HEALTH CARE

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ABSTRACT

The purpose of this article is to discuss some of the more challenging issues associated with conducting simulation in healthcare. The current healthcare environment is ripe for the use of simulation. The pressure to control costs is higher than ever, so, there is a critical need for powerful tools which can help clinicians and administrators (our clients) make good decisions on how to achieve objectives of reducing costs while maintaining high quality care. In addition, the highly stochastic nature of disease processes, as well as the complexity of subsystem interactions, makes simulation the decision-support tool of choice for analyzing the organization and delivery of healthcare services.

However, for simulation to reach its potential as a major weapon in the fight against spiraling healthcare costs, pragmatic approaches to several challenging technical questions must be offered and discussed. Therefore, this article will present approaches to dealing with the following, frequently encountered tactical issues in simulating healthcare services--degree of model complexity, definitions of input distributions, model validation, and interpretation of findings. The last issue to be discussed is less of a technical concern, and instead addresses the promotion of simulation in healthcare.

1 INTRODUCTION

The purpose of this article is to discuss some of the more challenging issues associated with conducting simulation in healthcare. Healthcare is a somewhat difficult arena in which to conduct simulation studies for a number of reasons. A panel discussion at the 1994 Winter Simulation Conference (Hakes et al., 1994) offered several interesting insights into the barriers associated with implementing simulation in healthcare, including the following:

- Historical disincentives to control costs. (This is changing!)
- Healthcare managers' traditional reliance on simpler, deterministic analytic techniques for decision-making.
- Administrators' and providers' resistance to the unfamiliar and dehumanizing nature of simulation.
- Highly technical nature of simulation.
- Number and variety of customers with competing priorities for solutions suggested by simulation.

Despite the existence of these barriers, the current healthcare environment is ripe for the use of simulation. The pressure to control costs is higher than ever, so, there is a critical need for powerful tools which can help clinicians and administrators (our clients) make good decisions on how to achieve objectives of reducing costs while maintaining high quality care. In addition, the highly stochastic nature of disease processes, as well as the complexity of subsystem interactions, makes simulation the decision-support tool of choice for analyzing the organization and delivery of healthcare services.

However, for simulation to reach its potential as a major weapon in the fight against spiraling healthcare costs, not only must the barriers discussed in 1994 be overcome, but pragmatic approaches to several challenging technical questions must be offered and discussed. Shuman and Wolfe (1992), in their assessment of the status of simulation in healthcare, write:

> Building a simulation model may be the easiest part of the process; addressing the tactical concerns of simulation, designing a valid simulation experiment and conducting a rigorous analysis of the results remain sophisticated endeavors. We have a fear that these factors are being increasingly overlooked by would-be modelers.

Therefore, this article will present approaches to dealing with the following, frequently encountered

tactical issues in simulating healthcare services--degree of model complexity, definitions of input distributions, model validation, and interpretation of findings. The last issue to be discussed is less of a technical concern, and instead addresses the promotion of simulation in healthcare.

Finally, it should be noted that this article is not a review of the applications of simulation in healthcare. Others have offered extensive bibliographies of such applications (Klein et al., 1993; Valinksy, 1975); and it is not my intent to repeat or improve upon those discussions here. However, a review of these bibliographies is strongly recommended to those just embarking on a healthcare simulation project. While previous simulation applications are frequently not available for widespread use, one can always learn from the techniques used and the problems encountered by others.

2 MODEL COMPLEXITY

One of the barriers to implementing simulation in healthcare discussed at WSC '94 was the highly technical nature of simulation. This issue includes the perception that the time, effort, and skill involved in developing, validating, and then experimenting with a simulation model are not worth the expected benefits. The time and skill level required for model building is certainly decreasing as the power and flexibility of available simulation software increases. Nevertheless, the time and effort required to construct a valid model and conduct carefully designed experiments with the model can still be significant, even for analysis of a relatively simple system. Therefore, it is important that the effort not be lengthened with the development of a needlessly complex model. Especially today where the healthcare environment is in a state of such rapid change, we cannot afford to spend too much time developing models of systems that are going to be outdated as soon as they are completed.

In his keynote address to the 1993 Winter Simulation Conference, John Salt provided an excellent discussion of the benefits of keeping simulation models "constructively simple" (Salt, 1993). The rule of thumb is to develop as simple a model as possible that you think will meet the project's immediate objectives. You can always add to the complexity of the model later if necessary, generally without having wasted any time by first developing a simple model.

One example of an area for which the appropriate level of complexity must be decided is that of patient case-mix. Obviously the case-mix of patients moving through a healthcare system can be modeled at a tremendous level of complexity--e.g., down to the level of individual diagnosis, if necessary. Of course, the effort associated with modeling at this level of complexity is significant, as are the data requirements for defining the arrival time and input distributions associated with such a large number of patient categories.

The key to deciding on the level of detail required in case-mix categories is the objective(s) of the model. If one of the objectives is to enable investigation of the effects of changes in case-mix on system performance, then case-mix needs to be defined at the level at which current planning activities are performed. For example, if planning presently takes place by projecting workload by department (e.g., number of surgery patients, number of medicine patients), then case-mix need only be defined at that level. Or, if planning takes place by DRGs, then patients should be modeled at this level of specificity. But there is no reason to further subdivide patient categories beyond what your facility currently uses or plans to use in the near future.

Before embarking on a complex simulation study, one should always consider the option of using a simpler, analytic model. While simulation offers a number of important advantages over analytic models, often these simpler models will suffice. Especially if the objective of the project is to plan for average performance, and variability around the average is not of significant consequence, then an analytic model may be fine. For example, if the objective is to construct a model for determining the annual staffing requirements of a department or facility, then an analytic model comprised of average time requirements should be sufficient for calculating the number of full-time equivalent positions to budget for the year. However, if you are interested in determining how to schedule those positions on any given day or week, you may then want to consider use of a simulation model, because workload variability will play more of a role in scheduling decisions.

Similarly, the design of an operating room block scheduling system, which requires allocation of blocks of time to individual surgeons or groups of surgeons, can easily be accomplished using an analytic model and average operating room time requirements. Even variability can be investigated using an analytic model, if the objective is to look at the effect of only one or two parameters on that variability. For example, to determine how much operating room time should be set aside for emergency cases, by time of day or day of week, an analytic model which considers variability in emergency arrivals can be designed. Historical data on emergency arrivals can be collected, arrival time

distributions graphed, and a decision made regarding the desired probability of having a room available when one is needed. In contrast, if the effect of the interaction of multiple variables (e.g., emergency arrivals, variability in surgical procedure times, and a patient scheduling system) on resource requirements (e.g., operating room nurse staffing) is to be investigated, a simulation model is desirable.

3 DEFINITIONS OF INPUT DISTRIBUTIONS

Common input distributions in healthcare models include the arrival times of unscheduled patients and the service times of resources (e.g., providers, rooms, beds, equipment, etc.). Two choices are available for defining these input distributions: theoretical or empirical. Both kinds can be defined using distribution fitting software such as UniFit II (Law and Vincent, 1993). The advantage of empirical distributions is that they fit the data, which might not be adequately represented by a theoretical distribution. However, the advantage of theoretical distributions is that they are easier to use for planning purposes.

For example, if you want to determine the effect of a change in demand (i.e., arrival rates) or practice patterns (i.e., service times) on performance, you will need to define the change in the corresponding input distribution. If the input distribution is a theoretical one, the change is fairly straightforward (if one assumes that the shape of the distribution is likely to remain the same)--the distribution's parameters (e.g., mean and standard deviation) simply need to be revised. In contrast, if the distribution is empirical, the entire distribution must be redefined. When making workload projections, it is generally easier to think in terms of revising individual parameters than entire distributions.

In addition, for those facilities or projects with little available historical data for defining empirical distributions, it is possible to use theoretical distributions that have been found to adequately represent healthcare processes in previous research. For example, the exponential distribution is routinely used to model the arrival of emergency patients to healthcare facilities (Lowery 1991; Esogbue and Singh, 1976; Cooper and Corcoran, 1974; Kao, 1974; Clipson and Wehrer, 1973; Shonick and Jackson, 1973). The exponential process works well for interarrival times when there is little or no control over the arrival process (Schriber, 1991, p. 254). Length of stay in hospitals has been modeled using a variety of theoretical distributions; but it appears that the lognormal distribution has the most documented support (Lowery, 1991; Magerlein, 1978; Storer and Hancock, 1976; Whitmore, 1975; Thomas, 1968; Balintfy, 1962; Flagle, 1960). Both of these distributions, as well as many others, can be easily modeled in commercially available simulation software.

When using distribution fitting software to test the degree of fit between a set of actual data and a theoretical distribution, one must consider the tradeoff between obtaining a possibly better fit using an empirial distribution and the flexibility of using a theoretical one. Therefore, even though statistical tests may indicate a poor to fair fit of the data with any theoretical model, look carefully at the more subjective, graphical comparisons of the actual data with the best theoretical model--the fit may look very acceptable. Consider the accuracy of the data set as well--is it possible that system problems or deficiencies might be skewing or distorting the data and, in turn, preventing the theoretical model from matching the data more precisely? If you do not want to include all the system distortions as part of your input distributions (which is generally the case), the theoretical model may be more appropriate.

The bottom line for deciding whether a selected input distribution, theoretical or empirical, is adequate for a modeling effort is whether the model eventually validates (see "Model Validation" below). If a model is not deemed sufficiently valid for its intended purposes, one may need to return to the assumptions underlying the definition of the input distributions. In contrast, a valid model provides some evidence that the selected input distributions are adequate, even if they do not precisely match the actual data from which they were derived. There is a need for more published research on the results of fitting actual healthcare data to theoretical distributions, and on the contribution of these distributions to model validity, to help other modelers who do not have access to historical data for performing their own distribution fitting.

4 MODEL VALIDATION

Many clinicians and administrators doubt the capability of computer models to capture the complexity and unpredictable nature of healthcare. Yet it is precisely these characteristics which lend themselves to modeling through simulation. One possible explanation for the lack of credibility of simulation models in healthcare applications is the limited attention modelers often pay to the model validation process. Demonstration of a simulation model's validity--i.e., its ability to accurately represent the system under investigation--is key to the acceptance of simulation as a technique. However, if

published studies are any indication of the level of effort that goes into the validation component of modeling efforts, it is little wonder that simulation as a technique still meets with some skepticism.

Few of the published results of healthcare simulation efforts offer much insight into the results of validation, let alone the validation process itself. This is unfortunate, because many of the textbook recommendations for validating simulation models do not lend themselves easily to healthcare applications. (See tutorial on "Model Validation" elsewhere in these *Proceedings* for more detailed information on validation techniques.) For example, recommended techniques of confidence intervals and hypothesis testing require independent observations. Many of the measures of interest in healthcare applications--e.g., average daily census of inpatient units, utilization of inpatient resources by day of week, patient waiting times for outpatient services by time of day--are strongly autocorrelated.

While it is possible to generate independent observations of these measures from simulation model output using such methods as batched means, it is often very difficult to use the same techniques for obtaining the real-world data for comparison, due to limited availability of these data. Performance data on healthcare systems are becoming increasingly available with the widespread implementation of computer-based information systems; but even with the implementation of these systems, the rapidly changing nature of healthcare today often precludes the availability of data for an extended period of time under the same set of input conditions. (An objective of validation is to compare a sample of model observations with a sample of actual observations under the same set of input conditions.)

Another problem with use of hypothesis testing as a method of validation is that because a simulation model is only an approximation of an actual system, the null hypothesis that model behavior and system behavior are the same will almost certainly be false (Law and Kelton, 1991, p. 312), especially when modeling such complex systems as healthcare applications. While formal statistical tests may lead to the conclusion that a model is not an accurate representation of the real world system under investigation, the model may still be valid for the purpose for which it is intended. This is especially true for models that are designed primarily for comparing alternatives than for predicting absolute answers.

However, the fact that it may be difficult or even impossible to develop a model that passes traditional statistical tests of accuracy does not at all preclude the need to conduct as thorough a validation as possible and justify a conclusion of model validity. Subjective validation techniques can be used and are discussed elsewhere in these *Proceedings* by Sargent (see "Some Subjective Validation Methods Using Graphical Displays") and Lowery (see "Design of Hospital Admissions Scheduling System Using Simulation"). Publication of validation methodologies and conclusions would go a long way in helping others design studies and interpret findings for healthcare applications.

5 INTERPRETATION OF FINDINGS

This section discusses two concerns that frequently arise when clinicians and healthcare managers review the results of simulation models. Unfortunately, there are no solutions to these concerns. I can only present the warning that they may occur and offer suggestions for words of reassurance. The two concerns are that (1) simulation does not provide the single, best answer to the problem at hand; and (2) simulation models do not predict the future. These statements may seem obvious and simplistic to researchers, management engineers, and statisticians who frequently work with simulation models. But they are not apparent to those most interested in the findings from these models--especially if simulation has been touted as the be-all and end-all solution to the problem at hand. Thus, while we certainly want to promote simulation as an effective decision-support tool, we must be careful to also explain its limitations.

Unlike analytic models, simulation models do not automatically provide the single, optimal solution to the problem under investigation. Instead simulation provides answers to "what if" questions via a series of trial and error experiments; or the results of simulation experiments are analyzed using such statistical techniques as analysis of variance, to determine the relationships between independent and dependent variables of interest. These approaches may disappoint some clients, who want a model that can provide *the* answer to their question, and quickly. The idea of having to review lots of output, only to decide that values of the input variables should be revised and the model rerun to see if performance can be improved further may not be very appealing.

With some explanation and encouragement, clients can be shown the advantages of the iterative and experimental approach of simulation over the use of analytic models which provide a single, "optimal" solution. The biggest advantage is that simulation models allow for the consideration of multiple, often competing performance objectives. Efforts to reduce healthcare costs cannot be implemented at the expense

of compromising quality. Thus, it is critical that an investigation of the effect of any change in resources or procedures include the examination of multiple performance measures. In contrast, analytic models generally accommodate single objectives subject to constraints on other objectives. Unfortunately, managers may not know the values at which the constraints should be set, because they may not understand the nature of the tradeoff between competing objectives. Simulation allows the explicit review of these tradeoffs.

For example, the decision to allocate beds among clinical services requires the consideration of the tradeoff between maximizing the utilization of beds (and associated costly resources such as staff and equipment) and minimizing adverse occurrences such as turning patients away because of lack of available beds. If managers could set one of these objectives at a desired maximum or minimum level to serve as a constraint—e.g., no more than 2 turnaways per month—then it would be a relatively straightforward process to determine the number of beds required to maximize utilization at that level.

However, managers are often unable or unwilling to set constraints, until they can see the relationship between the performance measures—e.g., by accepting an additional turnaway each month, how much of an increase in utilization can I obtain? Only after this relationship has been identified can decision-makers then determine what is acceptable. Simulation allows the examination of these tradeoffs, at the expense of some additional time and effort on the part of the decision-makers to experiment with the model. Once clients understand the importance and benefits of the experimentation process, hopefully they will embrace simulation as the powerful tool it is.

The other major "limitation" of simulation is its inability to predict the future. However, this characteristic can only be considered a limitation if predictive powers are expected. Therefore, it is important that managers understand up front that simulation is actually a "what if" tool. *What* would happen to performance *if* we changed values of the input variables. The values of the input variables must be specified. Unfortunately the values of the input variables must often be predicted, and simulation usually cannot help with this task.

In the previous example of bed allocation among clinical services, inpatient workload is a model input. If bed requirements for the next five years need to be determined, inpatient workload must first be predicted, and then the effect of that workload on bed utilization at various bed levels can be investigated (Lowery, 1992). On more than one occasion my clients have been disappointed to find out that the model does not predict inpatient workload.

While there is no actual solution to this problem, clients' disappointment and disillusionment can be mitigated by (1) explaining as soon as possible in the design process what the model will and will not do; and (2) offering sensitivity analysis as a way of diffusing the issue. Sensitivity analysis allows one to determine which input variables are the most important in terms of their ability to affect a change in the model's performance measures. Variables for which small changes in their values result in large changes in model performance should receive significant care and attention in measuring their true magnitude. Conversely, less time and effort should be spent collecting data on variables to which the model is not sensitive.

Thus, if a client expresses concern that a simulation model will not provide much useful information because future values of the input variables cannot be predicted, the answer is to encourage the use of sensitivity analysis. Results of the analysis may indicate that the input variables most difficult to predict have little effect on performance, thus leaving a wide margin for error in predictions. On the other hand, if results show that model performance is sensitive to a particular variable, then sensitivity analysis will at least provide the client with information on the magnitude and nature of the effect of the variable. Such information can provide an incentive to expend resources on input data collection or estimation, and can be helpful in the decision-making process even if accurate predictions are not possible.

6 PROMOTION OF SIMULATION

The promotion of simulation should not be limited to extolling its virtues as a "what if" experimentation tool. It can also make extremely valuable contributions to decisions by serving as a means of documenting assumptions, organizing the decision-making process, and identifying potential problem areas—regardless of whether or not the model is actually ever run. It is amazing how much time is spent in the planning process (especially in meetings) arguing over differences of opinion, where these differences are due to disagreements over assumptions never actually stated or acknowledged. Without a structure for identifying and documenting the numerous assumptions underlying decisions, it is impossible to conduct a meaningful discussion of the alternative solutions. The process of designing a simulation model provides such a structure. Documenting

assumptions in this manner enables all participants to start discussions with the same set of information, which in turn, significantly improves the efficiency of the decision-making process. While disagreements may still ensue over the content of the assumptions, the arguments become very clear and focused when the assumptions are in black and white in front of all participants.

Similarly, designing a model forces the decision-making process into a very defined format, which can assist in organizing the process. Finally, one of the frequently cited benefits of simulation is that the knowledge gained during the actual design process may suggest improvements in the system under investigation (Banks and Carson, 1984). Designing a simulation model requires a thorough investigation and documentation of current processes, which can identify unexpected problems unrelated to the original objectives of the study. Solutions to these problems may be readily apparent and relatively easy to implement, without the assistance of the simulation model.

Thus, it is not necessary to commit to a full-blown, large-scale simulation project to be able to realize benefits from the modeling effort. If clients are concerned with the time and effort involved in simulation, the intermediate benefits should be emphasized. Mahachek (1992) explains that one of the major barriers to the implementation of simulation in healthcare is the perception that "simulation is an *additional* layer of effort rather than an *organizer* of all your current efforts." He goes on to explain that, "Simulation is not a chasm which can only be crossed with one all-consuming leap. It can be nibbled at." And each of those nibbles can yield some benefit. I hope the suggestions provided in this article will serve to ensure the achievement of those benefits.

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