Proceedings of the 1998 Winter Simulation Conference
D.J. Medeiros, E.F. Watson, J.S. Carson and M.S. Manivannan, eds.

GETTING STARTED IN SIMULATION IN HEALTHCARE

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ABSTRACT

To begin using simulation in healthcare, one must first recognize the types of problems or decisions that can best be analyzed using simulation. Once a problem has been identified, a well-established series of steps for attacking a simulation problem should be followed. The first half of the discussion will focus on identifying applications, to help identify the problems amenable to solution by simulation. Specifically, a description of applications in the following two major categories is provided: (1) "analytic" decisions with uncertain components; and (2) comparison of alternative systems for determining resource or scheduling requirements. The second half of the discussion will include recommendations for some of the steps in conducting a healthcare simulation project, including model building; data collection, setting assumptions, and documentation; validation; reporting results; and implementation.

1 IDENTIFYING APPLICATIONS FOR SIMULATION IN HEALTHCARE

Simulation is an extremely useful tool for modeling uncertainty, which is a major characteristic of illness and, hence, makes simulation so attractive for modeling healthcare systems. In addition, simulation enables the modeling of complex systems with lots of interacting parts, which is another common feature of healthcare systems. Given the many potential applications of simulation in healthcare, it might be useful to categorize these applications, to help identify the problems amenable to solution by simulation. Healthcare applications tend to fall into two major categories: (1) "analytic" decisions with uncertain components; and (2) comparison of alternative systems for determining resource or scheduling requirements. To focus the discussion of these two types of applications, certain types of simulation models are excluded, as explained below.

The categorization includes stochastic simulation models and excludes deterministic models. Stochastic models contain probabilistic (i.e., random) components, while deterministic models do not. Only stochastic models are included in this discussion, because these types of models generally provide more accurate and informative representations of health care systems, given the random nature of illness and its response to treatment. However, the term "simulation" in the broadest sense refers to the operation of a model of a system, and there are many mathematical models of systems that do not include stochastic components. Therefore, readers will see many articles in the healthcare literature in which the term "simulation" is used when it refers to a deterministic model.

The categorization also excludes applications for which continuous simulation is used. This type of simulation involves modeling of a system in which the input variables change continuously with respect to time, and these changes are typically defined by differential equations (Law and Kelton, 1991). Continuous simulation is frequently used for modeling biological processes and pharmacokinetic applications (e.g., Thomaseth and Boniollo, 1996), but has also been used for epidemiologic models of disease progression (e.g., Bongaarts, 1989). Continuous simulation models are not included here, since the focus of the discussion is on the application of simulation for improving the organization and delivery of care.

1.1 Analytic Decisions with Uncertain Components

"Analytic" decisions are those that can be made by solving a mathematical equation or formula. When the values of the variables making up the equations or formulas are uncertain, they can be modeled using probability distributions and simulation. Examples of these include cost calculations, demand or population projections, break-even analysis, and inventory control calculations. An example of a software product that can be added to Excel spreadsheets for conducting simulations is @RISK (1998).

Austin and Boxerman (1995) provide an example of using simulation to perform break-even analysis. The probabilistic variables in this model are cost data, because their future values are uncertain. Cameron et al. (1998) explain an interesting use of simulation for determining potential costs and savings attributable to implementation of a telemedicine system in West Virginia. Their model has several input variables for which probability distributions are used due to uncertainty, including the payment-to-charge ratio for services provided, proportion of use of the system for inpatients, incremental demand for specialists, and reduction in hospitalization rate due to the system. An example of the projection of the incidence of a disease (monkeypox) by a simulation model, which can be used for estimating demand for resources, is provided by Jezek, Grab, and Dixon (1987). Their probabilistic variables include number of close contacts with the virus, vaccination status, and infection status.

Hofer and Hayward (1996) use an analytic model and simulation to evaluate the ability of mortality rates to detect hospitals with quality problems. The model simulates the number of discharges in their hospital sample, the number of deaths, the proportion of deaths due to nonquality-related factors, and the proportion of deaths due to potentially preventable (quality-related) factors. Interestingly, they conclude that hospital mortality rates cannot accurately detect poor quality hospitals using medical diagnoses, due primarily to the large variability in mortality rates across hospitals and to large, unmeasured case-mix differences among hospitals. Simulation is the perfect tool for modeling these highly variable hospital characteristics. The authors use the results of this work to recommend that health care systems discontinue the use of mortality data in hospital "report cards."

Simulation can also be used for modeling input to more complex types of analytic decisions, such as those employing Markov models or decision trees, which are often used for representing patient flow through various disease states. These simulations can be used for determining the effects of various interventions on the morbidity, mortality, and/or treatment costs of a population. An example of software specifically designed for this purpose is Decision Analysis by TreeAge (DATA™, 1996). Examples of these types of applications include an analysis of prevention strategies for non-insulin dependent diabetes mellitus (Eastman et al., 1997); a comparison of the cost-effectiveness of screening mammography in women of different age groups (Salzmann, Kerlikowske, and Phillips, 1998); and prediction of performance of heart valve replacements (de Kruyk et al., 1998).

1.2 Comparison of Alternative Systems for Determining Resource or Scheduling Requirements

Much of the challenge we face in healthcare today is how to improve the efficiency of operations—i.e., determining the best way to organize the multiple resources required for the delivery of care. Determining how to allocate and schedule these resources can rarely be performed with the aid of a simple formula. Instead, managers and clinicians think of these decisions as systems consisting of complex relationships among interacting variables. Simulation is very useful for modeling these types of complex systems. Use of simulation for these purposes is different than using it for modeling analytic decisions, in that the analysis of operational systems generally requires a comparison of alternative systems to obtain the desired information. (In contrast, the "solution" to an analytic decision can be obtained by modeling a single set of relationships among the variables of interest, defined as a formula.) In addition, the model is defined not in terms of a series of equations, but in terms of the physical movement of a transaction (e.g., patient, lab test) over time through different facilities or resources.

For example, when using simulation to determine how many resources (e.g., hospital beds, operating rooms, examining rooms, x-ray machines, nurses, physicians, technicians, etc.) are needed for a healthcare facility, there is no formula that combines different variables (e.g., demand, utilization, etc.) to equal "number of resources required." Instead, the simulation model includes resources as one of the input variables, and the analyst must try different values of the input variable(s) and examine the effects of these values on the output variables of interest (e.g., utilization, delays in service, turnaways, etc.). Different values are tried until one is found that produces acceptable performance (as measured by the output variables). Thus, when using simulation to determine resource requirements, an experiment must be designed to compare alternative systems (e.g., different resource levels). Simulation will not provide a single, optimal solution, unless simulation optimization software is employed in conjunction with an experimental design which examines a range of input values in a systematic manner (Carson and Maria, 1997).

Most of the published papers on simulation in healthcare are included in this category. Klein et al. (1993) provide an extensive bibliography of examples of operational applications of simulation, as does the MedModel Web site (1998).

A subset of this category of applications is the use of simulation for business process reengineering. This is mentioned as a separate subcategory, because the objectives of these types of applications can be different than determining resource or scheduling requirements, even though the simulation techniques are essentially the same. There has been a lot of interest in recent years across all types of businesses, including healthcare, in the concept of change management. Many programs have been initiated in healthcare organizations in the areas of Continuous Quality Improvement (CQI) and Total Quality Management (TQM). These programs require businesses "to model the ways in which they currently operate, to identify opportunities for change, and to design and implement alternative ways of carrying out business processes" (Giaglis, Paul, and Doukidis, 1996). Simulation is an extremely useful tool for performing these activities. Therefore, to meet the growing interest in these approaches to improving business operations, separate software packages have been developed specifically for these types of applications, such as SIMPROCESS (Swegles, 1997) and Optima! (Palisade Corporation, 1998).

In business process reengineering, a simulation model of current processes can be constructed, then used to identify bottlenecks and underutilized resources. Bridgeland and Becker (1994) provide a list of kinds of analyses and "telltale statistics" that they have found to be useful in identifying problems with current processes based on simulation output. Diagnosing problems is the first step in determining how to change the system to improve performance. Proposed changes to the system may include a change in resource levels or scheduling; but they frequently involve a reorganization of processes—e.g., change from centralization to decentralization (or vice versa), elimination of one or more steps, introduction of automation, etc. Simulation can then be used to model the proposed, improved system before it is actually implemented, to see if the magnitude of improved performance is as expected.

2 STEPS IN DEVELOPING AND EVALUATING A SIMULATION MODEL

Banks and Carson (1995) describe the steps in a simulation study. They include: (1) problem formulation; (2) setting of objectives and overall project plan; (3) model building; (4) data collection; (5) coding; (6) verification; (7) validation; (8) experimental design; (9) production runs and analysis; (10) repeat of step (9) if necessary; (11) documentation of program and reporting of results; and (12) implementation of proposed system. (Steps 3 and 4 take place concurrently.) The following paragraphs present recommendations for accomplishing some of these steps when developing simulation models. The recommendations are probably applicable to all types of simulation models, not just those in healthcare; but they are based on experience with healthcare projects.

(3) Model building. Keep the model as simple as possible. 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. Banks and Carson (1995) note, "It is not necessary to have a one-to-one mapping between the model and the real system. Only the essence of the real system is needed." The simpler the design of the model, the faster it will get completed, the sooner you will have some results, and the happier your clients will be. (See step (11) below for additional recommendations on reporting results.)

(4) Data collection, *setting assumptions, and documentation*. I have added "setting assumptions" and "documentation" to Banks' and Carson's description of this step. Setting assumptions is one of the primary means to keeping a model simple. However, it is critical to document all of these assumptions, no matter now seemingly minor, so that your clients understand the model's limitations. If your clients start to balk at the assumptions, you can assure them that the assumptions can always be changed and additional complexities modeled if desired. Generally the clients understand the benefits of starting with a simple model, and simply knowing that any complexity can be added later will satisfy them.

Banks and Carson include documentation as step 11; but it is important to begin this process early, primarily for verifying assumptions with clients and ensuring they understand the data you are using as model input. For example, if you use your client's actual data on patient length of stay for 1997 as one of the model inputs, it is important to present summary statistics on these input data in your documentation for your clients to review. It is amazing how many different reports of length of stay can be floating around one hospital; and you want to be sure that your clients understand and agree with the specific statistics that you have obtained for model input.

Regarding data collection for model input, if your client does not have the necessary data for some of the required input distributions, seek out the staff who are most knowledgeable of the processes under investigation, and ask them to give you their best estimates of the parameters of the input data—e.g., mean, minimum, maximum, standard deviation, and shape of the distribution. In other words, make it up! This will often suffice for experimentation purposes, especially if there are no other options and your clients understand this is one of the model assumptions/ limitations. Also, consider conducting sensitivity analyses of distributions estimated in this manner. If model output is extremely sensitive to the estimates, then you may want to recommend to your client that they put some time and effort into initiating a primary data collection effort, or at least pay close attention to the estimation process.

(7) Validation. 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. Yet modelers often skip this step or give it limited attention, perhaps because validation is not an easy step and can be discouraging when a model does not validate initially. However, there is usually a good reason why a model does not validate, and it is important to identify and correct the problem before using the model to investigate the effects of changes to a system. The last thing you want is to make recommendations for a change in resource levels, scheduling, or organizational structure based on the results of an invalid model.

It is important to perform steps 6 through 9 (i.e., verification, validation, experimental design, and production runs) sequentially. It is certainly more interesting to experiment with the model than to spend time validating (which can be time-consuming and frustrating); but it is imperative that the model be verified and validated prior to any experimentation. Likewise, verification must take place before validation; there is no sense in spending a lot of energy trying to validate a model that has fundamental logic flaws.

(11) Reporting of results. Another reason for developing a simple model initially is so you can report results to your clients and obtain their feedback as soon as possible. Unless they are veteran users of simulation, your clients may have trouble envisioning the format or content of the results. (For example, they may be expecting you to tell them the number of operating rooms they need, when actually you will be giving them a page full of data on the utilization of each operating room.) After reviewing the initial output, their objectives for the project may change—and you do not want to have spent a lot of time in initial model development if that happens!

(12) Implementation. If you are fortunate enough to be around to see the results of a simulation model actually used for implementing change within an organization, consider collecting data on the effect of the change on the system's performance, and then comparing actual performance with model predictions. This comparison is an important type of model validation that is rarely done. When it is done, publication or presentation of the results would go a long way toward promoting the credibility of simulation models and the conduct of rigorous validations.

However, if you are placed in the unfortunate circumstance of being present when a change is implemented, but system performance is drastically different than that predicted by the model, do not panic! Investigate how model assumptions might differ from the actual system's characteristics, and compare the values of the input data used in the model with those of the actual system. One of the biggest challenges of simulation projects (not related to any limitations of simulation as a modeling technique) is the difficulty in predicting the future. When using simulation to determine the effects of proposed changes in a system, input data such as future demand for services must be estimated. If these estimates are inaccurate, model predictions will be incorrect as well. Therefore, a likely reason for observed discrepancies between model predictions and actual performance is a corresponding discrepancy between predicted and actual input data.

A more detailed discussion of the issues of model simplicity, data collection (input distributions), model validation, and reporting and interpretation of results is presented in Lowery (1996).

3 CONCLUSION

The current healthcare environment is ripe for the use of simulation. The pressure to control costs is higher then 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 delivery of healthcare services. However, to be able to use this tool effectively, healthcare managers must be aware of the types of problems amenable to simulation. Futhermore, modelers must understand the steps involved in initiating and completing a successful simulation project. I hope the information provided in this article will contribute to an increase in the effective use of simulation in healthcare.

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