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A TUTORIAL ON SIMULATION IN HEALTH CARE: APPLICATIONS AND ISSUES

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ABSTRACT

Simulation is an ideal tool for addressing wide ranging issues in health care delivery. These issues involve public policy, patient treatment procedures, capital expenditure requirements, and provider operating policies.

This tutorial presents example applications in each of these areas. Modeling, experimentation, and other project issues are discussed. A summary of technical issues, as well as issues relating to the acceptance of the use of simulation in health care delivery, is presented.

1 INTRODUCTION

Over the past four decades, simulation has proven to be a significant tool in the analysis of a wide variety of health care delivery systems. Over 30 years ago, Fetter and Thompson (1965) as well as Robinson, Wing, and Davis (1968), applied simulation to patient scheduling and other hospital operational problems.

Several characteristics of simulation make this technology uniquely applicable in the health care arena.

1. **Computer simulation models conform both to system structure and to available system data** (Pritsker 1989). Simulation models emphasize the direct representation of the structure and logic of a system as opposed to abstracting the system into a strictly mathematical form. The availability of system descriptions and data influences the choice of simulation model parameters as well as which system objects and which of their attributes can be included in the model.
2. **Simulation supports experimentation with systems at relatively low cost and at little risk.** Alternatives can be assessed without the fear that negative consequences will damage day-to-day operations as would be the case if experiments were conducted directly on existing, operating systems.
3. **Variation matters.** Variation has to do with the reality that no system does the same activity in exactly the same way or in the same amount of time always. If every aspect of every operation always worked exactly on the average, system design and improvement would be much easier tasks.

   Variation may be represented by the second central moment of a statistical distribution, the variance. For example, the times between arrivals to a drop-in outpatient clinic near its opening time could be exponentially distributed with mean 5 minutes and, therefore, variance 25 minutes. Variation may also arise from decision rules that change processing procedures based on what a system is currently doing or because of the characteristics of the patient receiving care. For instance, the examination time for a patient needing two sutures removed could be 5 minutes and for a patient receiving an annual physical could be 30 minutes.
4. **Simulation experiment results conform to unique system requirements for information.** Using simulation, the analyst is free to define and compute any performance measure of interest, including those unique to a particular system. Transient or time varying behavior can be observed by examining individual observations of these quantities. Thus, simulation is uniquely able to generate information that leads to a thorough understanding of system design and operation.

Simulation applications in health care delivery may be classified into four categories:

1. Public policy.
2. Patient treatment processes.
3. Capital expenditure requirements.
4. Provider operating policies.

In this tutorial, example simulation applications in each of these categories will be presented. One model per category will be discussed in detail. Simulation modeling and experimentation issues of unique importance in health care delivery applications are presented. Strategies for gaining acceptance of the use of simulation in health care delivery are discussed.

2 PUBLIC POLICY

Public policy applications have to do with evaluating strategies for delivering health care that are implemented in state or national policies.

Standridge, Pritsker, and Delcher (1978) described a simulation model for projecting the number of physicians, nurse practitioners, and physician's assistants in Indiana from 1975 through 2000 as well as the demand for primary health care. The model supported decisions concerning the number of students admitted to medical school and other practitioner training programs in the state of Indiana. A companion model (Hindle, et al., 1978) assessed the availability of primary health care in 99 service areas in Indiana at any single point in time. It was used to help identify underserved areas. Graduating medical students and residents agreeing to practice in such areas would receive financial assistance with medical education expenses.

Pritsker, et al. (1995) describe a simulation project to help establish national policy for allocating donor livers to patients needing transplants. The model helps compare alternative policies using performance measures such as percentage of patients receiving transplants for each liver disease status, patient waiting time for a transplant by disease status and region of residence, and the number of pediatric transplants. Sophisticated statistical analysis of patient demographic, disease status and transplant data was required to estimate model parameters.

In 1977, the State of Iowa decided to test capitation reimbursement in its Medicaid drug program in two rural counties (Standridge 1981a; Standridge, Fisher, and Tsai 1983; and Yesalis, Norwood, and Lipson 1982). Capitation is a system of reimbursement for services under which providers are paid a fixed amount per client served per time period. Pharmacists were not placed at financial risk since they could not control the demand for prescription drugs. The capitation payment was set at 90% of the projected drug expenditure. This amount was derived from historical data. A pharmacy that could control its costs to be less than the capitation payment increased its profitability.

The remaining 10% was set aside in an escrow account. Any pharmacy that received less under capitation than under fee-for-service for the total amount of service provided could request reimbursement of the difference from the escrow account. The balance in the escrow account at the end of the experiment was the cost savings to the government due to capitation. The results of this experiment were positive.

The experiment was expanded to include a large population of Medicaid eligibles especially those residing in metropolitan areas. The research team wanted to demonstrate that cost savings were feasible and that pharmacy reimbursement would be adequate but not excessive before the expanded phase was conducted. Simulation was chosen as the demonstration vehicle.

The simulation was implemented in four components linked by an SDL database (Standridge 1981b). The database stored all the input data needed by each component and stored the results produced by each component. The results produced by one component could be input to another component.

The first component was a FORTRAN program that generated histograms of quarterly eligible drug costs from data concerning Medicaid eligible drug usage and cost taken from the Medicaid Management Information System.

The second component was a simulation model written in FORTRAN to that produced a randomly generated clientele for one pharmacy. Each patient was characterized by age, gender, and institutionalized status (YES or NO).

The cost generation simulation model, written in the GASP IV simulation language (a precursor of SIMAN and SLAM), used the outputs of the two previously discussed components as input. The quarterly prescription drug cost for each patient was output.

The fourth component was a set of FORTRAN programs that computed various performance measures from the results of the cost generation simulation model. These performance measures were defined and computed over time through on going discussion among the research team.

Key performance measures were the percent of quarters when the supplemental payments exceeded the escrow account and the percent of quarters when pharmacies made a windfall profit.

Results showed that the minimum cost savings that a successful Medicaid drug program capitation system needed to achieve was 10%.

3 PATIENT TREATMENT PROCESS

Standridge and Brown-Standridge (1995) as well as Brown-Standridge, Standridge and Poole (1993) describe the use of simulation to assess a new family therapy process called Brief Systems Family Therapy (BSFT).

Typically, family - therapist interactions occur weekly during a therapy session of about one hour duration. The therapist directs the session and constructs "interventions," planned modifications of dysfunctional cycles, to help family members toward improved behaviors in their relationships. Major interventions broadly include whatever message or instructions the therapist leaves with the family at the close of each session. Thus, the therapist must manage a session to arrive at a meaningful major intervention within the one hour time limit. Furthermore, what is accomplished in one session may influence the process of subsequent sessions.

The family therapy process is difficult to discern since interactions consist of intangible elements. Family therapy is talk therapy, so process steps are embedded in verbal interactions and may be impeded by non-productive verbal exchanges. Therapist decisions about the timing and sequence of process steps for each family are based not only on the words of family members but on their subtle, nonverbal movements and facial expressions as well.

Six checkpoints in the new BSFT process were specified.

1. Problem Formation: the activities that help narrow and more clearly specify each family member's original problem, and thus rework it into a treatable form.
2. Solution Formation: the activities that help narrow and more clearly specify each family member's notion of improvement such that the original problem focus can lead to a more hopeful solution focus.
3. Enactment Formation: in-session family interaction that makes it obvious how open and capable individual family members are of trying new behaviors.
4. Hypothesis Formation: identification of known patterns of interaction, speculation as to "missing links" in those behavioral patterns that remain obscure, and making the best prognosticative judgment as to what the clients could handle differently toward disrupting dysfunctional patterns by the next session.
5. Task Intervention Formation: the decision rules for intervention based on information derived from the first four checkpoints and previous sessions.
6. Follow-up: the therapist's initial assessment of the results of the intervention given at the end of the previous session.

Integrating these checkpoints into a process means specifying the decision rules for moving from one checkpoint to the next and explaining what information from preceding checkpoints is most useful in reaching following checkpoints. Accomplishing this requires specifying detailed steps between each checkpoint and how to move from one step to another.

Consider how the simulation model of this processes describes the problem operationalization step of the problem formation checkpoint. In this step, the therapist steers the discussion toward advanced precise problem definitions that include specific problematic behaviors for the couple. It is preceded by the problem consensus step that aims at bringing about agreement between family members as to a new definition of the problem that puts them both "in the same boat," rather than at odds with each other.

The therapist attempts to guide the husband and wife to each be as specific as possible about the behaviors associated with their interactional problem. In the simulation, this is modeled with two state variables, one for the husband and the other for the wife, with a value of 100 for perfectly specific and a value of 0 for perfectly vague. The therapist must decide how specific the husband and wife must each be before moving to the next sub-step in the process. Initially, the husband is approximately 1/3 to 2/3 specific with the wife slightly more specific. This specificity is lessened by the percentage of the desired consensus achieved in the previous step. That is, the less consensus achieved, the less specifically operationalized the husband's and wife's joint problem will be.

Typical of many steps, the therapist begins a cycle of assessment of the couple, followed by a decision point, followed by a therapeutic question. If both the husband and wife are sufficiently specific, the therapy process moves on to the next sub-step, Problem Sequence. If the session is close enough to the end of the hour, the therapy process must continue with the hypothesis formation checkpoint. The type of task intervention constructed depends on the checkpoints and steps preceding the hypothesis formation checkpoint. Otherwise, the therapist asks the couple a therapeutic question that can result in the specificity of operationalization going up or down. Therapist's expectations of husband and wife specificity go down as the cycle must be repeated more often. This implies that moving on to a subsequent step is more beneficial that getting stuck on one issue and risking that the couple will become frustrated with the process.

It is difficult to observe and measure data concerning the changes of specificity of individuals under any conditions. Thus, these values were estimated by expert opinion. Experienced therapists gave the following:

1. The average number of therapeutic questions needed to achieve specificity.
2. Husband and wife specificity can change in a negative or positive way in response to a therapeutic question, but far more likely positive than negative.
3. The therapist lowers specificity expectations to avoid getting stuck at any one checkpoint in the process. It is thought to be more therapeutic to move on to the next therapy checkpoint even if initial therapist specificity expectations are not met than to continue to discuss a particular issue without progress and risk client frustration with the process.
4. Typically, husbands and wives are not very specific at the start of a step.
5. There is variability in all aspects of a step.
6. The clock time to complete one cycle is minimally about 2 minutes.

Initial husband and wife operationalization specificity values, therapist expectation of specificity values, and change in specificity values were set to be consistent with the above.

The simulation results addressed the main issues concerning the new BSFT process:

1. Demonstrating to therapists how typical family therapy sessions might proceed.
2. Assessing if all of the process steps could be accomplished in one session.

The simulation was run for one hundred families, each of which participated in eight therapy sessions. In 87% of the sessions, solution formation was not completed before hypothesis formation needed to start. Thus, it was decided to test an alternate process under which the therapist would start with solution formation if problem formation was successfully completed in the previous session. For this case, 50% of the sessions completed the three major checkpoints before the time hypothesis formation needed to start. Thus, this latter approach was adopted.

4 CAPITAL EXPENDITURE REQUIREMENTS

Determining the level of capital expenditure for equipment needed to effectively provide patient care is an important application area for simulation in health care delivery.

Steward and Standridge (1996a, 1996b, and 1996c) describe a simulator for helping to establish the resource requirements of a small animal veterinary practice.

Spatial resources are predominantly reception/waiting, examination, treatment and surgical areas. These areas may overlap as multipurpose stations but the different uses impose peculiar constraints (for instance dental procedures generate a large number of airborne contaminants incompatible with sound pre-operative or surgical procedures using the same location in the facility) or timing (a patient prepped for surgery should not be postponed from surgery by unrelated events in order to minimize anesthetic cost and risk). Equipment resources vary widely. Everything necessary to treat and prevent disease, from grooming to dentistry equipment to proctoscopy, is required inventory. Rapidly changing technologies of medicine impact the economics of the practice with costly equipment obsolescence simultaneous to an expanding instrumentation list calling for efficient utilization.

Personnel required may be categorized into receptionist/office management, animal technicians, and professionals but the roles played by each frequently overlap. Although the organization of responsibilities is useful, random behavior of the patients and medical events require frequent deviations and/or adaptive policies for prioritization.

Demands for service happens with observable frequency distributions but do not allow rigid scheduling. The differing types of services are associated with differing demand profiles. When demands conflict, policies for resolution determine suitability of outcome and impact performance in a variety of ways. Scheduling is important to render some order to the potential chaos resulting from random behavior of patients and biological processes. A clever set of rules is required to provide adaptive flexibility for staff assignments, prioritization and decisions in the real system and therefore to simulate such systems.

Thus, a unique aspect of this simulator is that the scheduling of appointments is modeled using an expert system. There are four types of rules expressed in IF—THEN statement form: appointment-type-compatibility, appointment-time-determination, temporal-constraint and current-time.

Appointment-type-compatibility rules help manage the assignment of health care delivery system resources to patient care tasks. These rules seek to maximize resource utilization while avoiding conflicting assignments to concurrent tasks. For example, an outpatient examination cannot be scheduled to begin concurrently with an outpatient surgery since the veterinarian requires a significant amount of time to perform both. However, an outpatient examination can be scheduled to begin concurrently with an outpatient non-surgical treatment if a technician can perform significant parts of that task.

Appointment-time-determination rules specify how to search the appointment calendar to determine an appointment time. The search strategy tries to minimize the difference between the desired appointment time specified by the health care provider and the actual appointment time.

Closed-facility rules define the time when the facility is closed as incompatible with all other appointment types. Current-time rules forbid the scheduling of an appointment prior to the current simulation time.

Simulator input variables quantified the demand for different types of services, the arrival patterns of patients, and the amount of system resources available as well as giving operational policy parameter values.

Simulator outputs included the utilization of spatial, equipment and personnel resources as well as time delays encountered by patients receiving treatment.

5 PROVIDER OPERATING POLICIES

There are many applications of simulation to operational policies of health care providers. Typical projects are reported by Butler et al. (1992), Chan and Metzger (1993), Dittus et al. (1996), Dumas (1984, 1985), Evan, Gor, and Unger (1996), Klee, Standridge, and Nath (1980), Kwak, Kuzdrall, and Schmidt (1976), Lopez-Valcarcel and Perez (1994), Lowery and Martin (1992), Mahacek (1992), Vissilacopoulos (1985) and Wright (1987).

An application of simulation to emergency room operating policies present by Garcia et al. (1995) is discussed in detail. At issue was the excessive length of time non-urgent patients waited for care in an emergency room at an non-profit hospital. Current policy gave such patients the lowest priority for service. An alternative policy was proposed whereby staff and emergency room resources were dedicated to the care of non-urgent patients.

This policy is referred to as a fast-track for non-urgent patients. It is implemented by dedicating one emergency room bed to these patients. This bed is referred to as the fast track bed.

The emergency room serves five types of patients: ambulance arriving patients and non-ambulance arriving patients further classified as emergency, urgent, non-urgent, and stable.

Upon arrival, a non-ambulance patient must proceed through registration and then triage where the patient is classified into one of the four sub-categories. The patient then returns to the waiting area until a bed is available. At that time, treatment begins.

When a patient arrives by ambulance, a bed is assigned immediately and treatment begins. Registration is performed in parallel with the beginning of treatment. The ambulance contacts the hospital while enroute. If no bed is available, the ambulance is directed to another hospital.

Waiting patients are ordered by their severity of their medical need. Ambulance patients are served immediately. Emergency patients are served before urgent patients and so forth.

If many ambulance, emergency, and urgent patients arrive in a short time period, non-urgent and stable patients may wait for an excessive amount of time. Management wishes to serve patients in all categories as expeditiously as possible. Thus, an alternative that provides non-urgent and stable patients with a shorter stay in the emergency room was sought.

The time between patient arrivals is exponentially distributed with a mean of 18 minutes between 8:00 A.M. and 10:00 P.M. and with a mean of 49 minutes between 10:00 P.M. and 8:00 A.M. Of the total number of patients, 25% arrive by ambulance. Of the non-ambulance arriving patients, two-thirds are equally divided among emergency and urgent and the remaining third are equally divided among non-urgent and stable.

There are nine total beds in the emergency room as well as one triage nurse and one worker in registration.

Significant modeling and experimentation issues in this project were the following:

1. Arrival rates varied by time of day.
2. Multiple sources of data needed to be rectified. Data concerning patient arrival times and total time in the emergency room were available from the hospital information system. Distributions were fit to this data using distribution fitting software. Data concerning the time to perform each component of service was gathered using time studies, interviews with doctors and nurses, and from hospital policy statements.
3. Non-urgent patients arriving when fast track resources were busy were routed to the urgent care area of the emergency room.
4. Some activities of doctors and nurses, such as the time to do paper work, were no included in the model do to a lack of data.

Results showed that the average time non-urgent patients were in the emergency room was reduced from 2 to 3 hours to less than 2 hours using the fast track policy.

6 MODELING AND EXPERIMENTATION ISSUES

The following are some simulation modeling and experimentation issues that are particularly significant in health care applications.

1. Voluminous data may require sophisticated statistical analyses in order to estimate model input values.
2. Data from multiple sources need to rectified in estimating model input parameter values.

3. There is high variability in patient care requirements that must be modeled with random variables or complex model logic.
4. Patient arrival rates can vary by time of day, day of week and time of month.
5. The only source for some model input values may be expert opinion.
6. Integration of multiple modeling techniques may be necessary for model building.
7. There may be high variability in model outputs due to the high variability in patient behavior and care requirements.

7 ACCEPTANCE ISSUES

The following ideas may help in overcoming barriers to the acceptance of the use simulation in health care delivery applications.

1. Make sure that the information provided by the simulation model has more value than the information provided by an expected value analysis that can be implemented on a spreadsheet.
2. Make sure that it is clearly understood that the simulation model includes the possibility of the random occurrence of multiple events in near time proximity that can make the system behave in the worst possible way.
3. Make sure that the simulation analyst participates as a full member of the project team and does not merely perform model building and experimentation tasks to support the team.
4. Make sure that all alternatives needed for a full evaluation of project issues are assessed.
5. Make sure that the model outputs are responsive to the information needs of the project team.
6. Make sure that the model includes all relevant components of the system operation.
7. Build and present a prototype model with illustrative results to the project team as soon after the start of the project as possible.

8 SUMMARY

This tutorial discusses the application of simulation in health care delivery. Particular characteristics of simulation modeling and experimentation that are especially useful in such applications have been identified. Four major categories of health care delivery applications have been defined and typical applications presented. Some modeling and experimentation issues unique to health care delivery applications were listed. Possible approaches to overcoming barriers to the use of simulation in health care delivery are given.

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