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AN INTRODUCTION TO USING COMPUTER SIMULATION IN HEALTHCARE: PATIENT WAIT CASE STUDY

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ABSTRACT

As healthcare continues to become more competitive, the ability to assess tradeoffs between resource utilization, service, and operating costs grows in importance, such as with respect to appointment access, waiting room delays, and telephone service. This paper discusses the use of simulation analysis for studying and improving these and other health systems. A case study concerning pediatric waiting times illustrates typical steps involved in a simulation study, possible types of analyses, and resources required. Other healthcare uses of simulation, pitfalls to avoid, and software selection also are discussed briefly.

INTRODUCTION

Computer simulation is one of the most widely used operations research tools presently available and is one of several methods used to evaluate, improve, and optimize many types of processes. Although simulation has been used in healthcare research for nearly three decades, the past five to ten years have witnessed a dramatic increase in use by non-academic healthcare practitioners. Additionally, common availability of personal computers and significant advancements in commercial software suggest that simulation will continue to become more widely used, both by technical and less-technical healthcare analysts.

As healthcare organizations strive to remain competitive, simulation can be an especially valuable tool in the increasing number of TQM/CQI and process redesign efforts. Moreover, common process problems throughout expanding hospital and managed care networks create opportunities for re-usable simulation models. For example, healthcare providers almost universally suffer from unacceptable waiting room delays (see the Nuffield Report, 1965) which could be addressed using simulation.

Role Of Simulation In CQI And Process Re-Engineering

Due to increasing complaints about long waiting room delays throughout an HMO, two approaches to understanding and reducing patient waits were piloted in a pediatric department. First, a "quality management" project developed an understanding of the pediatric patient-flow process, surveyed customer expectations, and used a classic "CQI" cross-functional team approach to brainstorm possible solutions. Although many improvement ideas were generated, considerable uncertainty and disagreement existed within the group as to which of the ideas would significantly reduce patient waits. Additionally, some proposed

changes would be expensive and time-consuming, such as schedule modifications and additional exam rooms or staff. Computer simulation, which offered a less expensive, less disruptive, and more timely means of evaluation, then was used to evaluate the impact of these proposed process changes on patient waits. Further information on this case study can be found in Benneyan *et al* (1994).

Establishing Baseline Measures And Targets

The amounts of time patients were spending in each process step were determined via several data collections. These baseline measures later were used to evaluate, via simulation, benefits of proposed improvements. Although initial data were collected manually and via stopwatch, hand-held bar code readers and special-purpose commercial software greatly simplified most data collection and analysis. By attaching bar coded stickers to each patient's paperwork, the exact times at which patients moved through the pediatric process (e.g., time patient entered exam room) were easily recorded. This analysis revealed that patients waited an average of approximately 26 minutes to see their primary provider, as shown in Figure 1, whereas a survey indicated that waits exceeding 15 minutes generally were unacceptable. Significant variability in exam duration also was found, as shown in the right-hand column of Table 1.

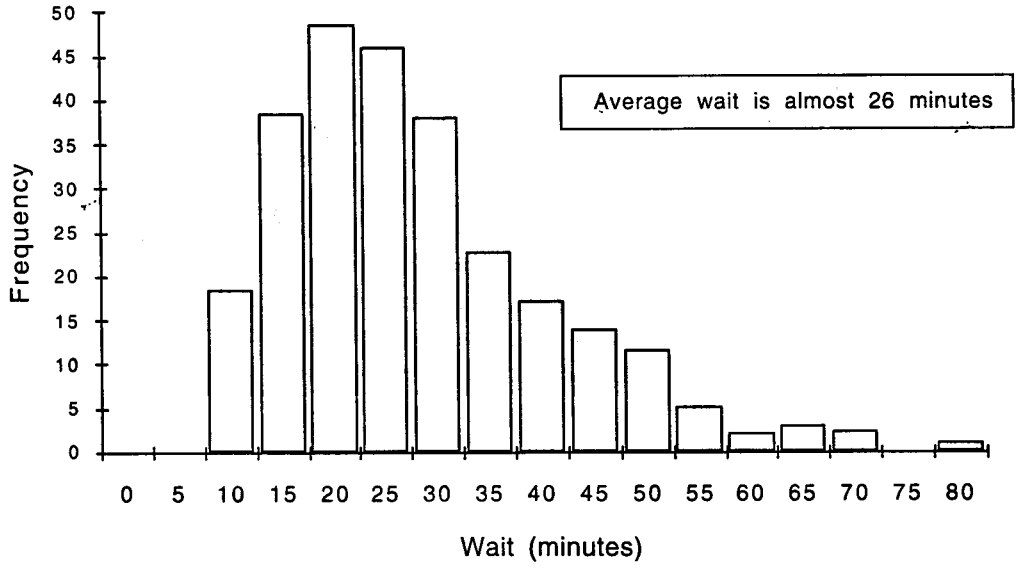

Figure 1: Distribution of Amount of Time Patient Waits for Provider

Table 1: Scheduled versus Actual Exam Duration

Scheduled Exam Duration	Actual Exam Duration	
	Average	St. Dev.
7.5 mins	8.50 mins	4.27 mins
10 mins	11.87 mins	9.85 mins
15 mins	15.70 mins	5.90 mins
20 mins	20.22 mins	11.12 mins
30 mins	28.00 mins	13.53 mins
40 mins	47.50 mins	7.50 mins

OVERVIEW OF COMPUTER SIMULATION

A simulation is the imitation of the operation of an actual process over time. By emulating the logic and randomness of a process, such as the flow of patients through the pediatric department and the random duration of each type of exam, a simulation is valuable for evaluating and comparing proposed process changes. For example, "*What if* more pediatric exam rooms were added?" Searching over a range of "*What if*" questions can lead to optimal decisions. The effects of process changes, such as additional pediatricians, are evaluated through performance measures, such as the amount of time (simulated) patients wait to be seen. As a simulation executes, many performance measures can be recorded for subsequent statistical analysis. The activity of the process also can be displayed on a computer screen as the simulation runs, offering a visual representation of the system. Although this sometimes is helpful for demonstrating simulation concepts to the unfamiliar, animation alone is not very useful for in-depth analysis.

Note that although several types of simulation exist, this article primarily is concerned with *stochastic discrete-event digital computer simulation*, which is one of the most common methods. Some other types of simulation include Monte Carlo (static), continuous, deterministic, mixed discrete/continuous, iconic simulators, and even manual simulation. In addition, some simulations can involve advanced and specialized topics beyond the intended scope of this article. Further information can be found in Banks and Carson (1984), Law and Kelton (1991), and Pegden, Shannon, and Sadowski (1990).

Historical Use of Simulation in Healthcare and Other Industries

Simulation has a long history of use for studying and improving healthcare systems. Roberts and English (1981) report that simulation was used to study emergency and non-emergency admissions as early as 1962. Frequency of use rose steadily through the 1960's and 1970's. For example, Shuman and Wolfe (1992) note that by 1975 over two hundred simulation healthcare studies had been reported in the literature, and in 1981 Roberts and English (1981) published a bibliography of 427 journal and conference citations. Simulation use continued to increase dramatically throughout the 1980's and 1990's, with special purpose simulation software and consulting services specifically marketed to the healthcare sector. More recently, an entire issue of the *Journal of the Society for Health Systems* (see Giglio, 1992) was dedicated to healthcare applications of simulation.

Common studies over this history have included capacity and hospital bed planning, outpatient clinics, critical care and emergency room settings, ambulance and other emergency medical systems, staffing and utilization, scheduling, patient flow and waits, regional planning, and others. For example, see Fetter and Thompson (1966), Rising (1973), Fries (1976), Pierskalla and Urban (1976), Wilt and Goddin (1989), and Pallen and Kittel (1992). A wide variety of non-healthcare applications also have benefited from simulation, including production systems, inventory systems, distribution networks, facility layout, scheduling, manpower planning, reliability and quality control. Non-manufacturing studies include weather patterns, forestry and game policies, disease and epidemic spread, population growth, welfare systems, pollution and other environmental issues, business forecasting, stock analysis, telecommunication, computer systems, military battles, airports, ski resort design, traffic congestion and signal timing.

Value of Simulation

In addition to acting as a *"What if"* tool as described above, unanticipated problems can be exposed before incurring costly and time-consuming investments, with simulation results periodically contradicting intuition. For this reason, some manufacturing companies will not permit a major operational change or a new facility to be built before first simulating the intended modification. Because it is useful simply as a sanity check or to verify other analysis, Pegden, Shannon, and Sadowski (1990) note that "management is increasingly viewing simulation as a very inexpensive insurance policy."

Other benefits include the ability to study data which may be difficult to obtain otherwise, such as to balance the percent of time various staff are idle. Additionally, computer simulation permits "time compression" so that "artificial" data can be quickly collected (from the program) which might take months or years to collect from the actual process. Although one drawback is the amount of personal and computer time sometimes required to develop and run a simulation model, continual advances in computer speed and general purpose simulation languages significantly reduce the programming burden and execution time. See Law and Kelton (1991) and Pritsker (1992) for additional discussion of uses, advantages, and disadvantages of computer simulation.

Simulation versus Other Methods

Rising (1973) and Roberts and England (1981) state that many healthcare systems can be viewed as some form of a stochastic (random) network, and Rising (1977) discusses simulation as one of several possible methods for analyzing proposed healthcare process changes, including queuing, Markov and other stochastic methods, experimentation with the actual system, and spreadsheet and deterministic models. A primary advantage of stochastic over deterministic methods is that they account for the existence of process variability, whereas basing analysis solely on averages ("management by average") can yield radically inaccurate results if significant variation exists. Because queuing and simulation methods are based on variability, therefore, they are more appropriate for modeling patient-flow processes.

For example, consider representing a single-provider 24-hour walk-in clinic with a simple M/M/1 queue, where patients arrive according to a stationary Poisson process at a rate of 4 patients per hour (one arrival on average every 15 minutes) and are treated at an exponential service rate of 12 minutes per patient (5 patients on average per hour). Based on these averages and deterministic reasoning, it initially might appear that such a process would have adequate capacity to treat patients with minimal waits. In reality, however, the queuing results summarized in Table 2 indicate that an average of 4 patients will be in the clinic, each for an average of one hour. Of these, an average of 3.2 patients will be in the

Table 2: Pitfalls of Management by Averages (M/M/1 queuing results)

Average # in Clinic	Average Time in Clinic	Average # Waiting	Average Length of Wait	Provider Utilization
4 patients	60 minutes	3.2 patients	48 minutes	80% utilization

*(*15 minute exponential interarrival rate, 12 minute exponential service rate)*

waiting room, each waiting an average of 48 minutes until they are seen. (Note that approximately half will wait longer.) Although the high provider utilization of 0.80 is desirable in terms of staffing, this is a poorly designed process in terms of patient waits and satisfaction.

While this simple example illustrates the importance of accounting for process variability, most queuing models are based on steady state and distribution assumptions, primarily the negative exponential and its relatives, which in reality frequently may not be met. For example, the exponential distribution shown in Figure 2 is a highly unlikely candidate for representing exam duration, whereas a log-normal or gamma distribution is much more probable; (see Roberts and England, 1981). Table 3 illustrates the significant changes in waits in the above example resultant from non-exponential exam duration (based on an M/G/1 queue). See Wolff (1989) for further information on queuing processes and underlying assumptions.

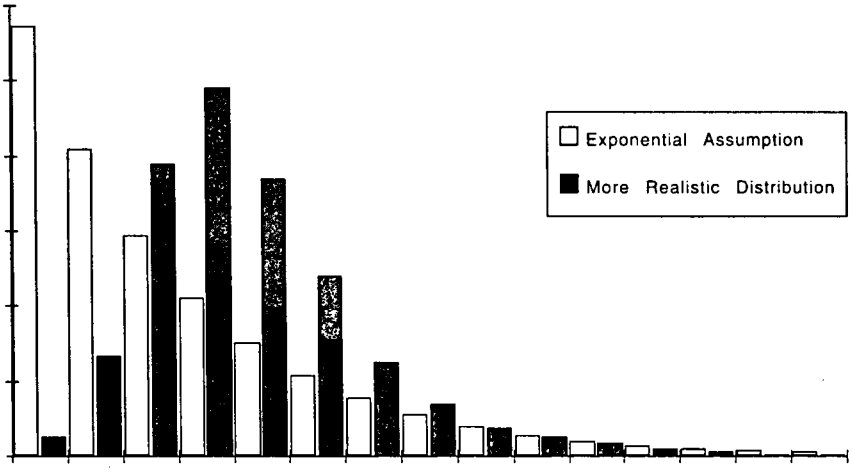

Figure 2: Standard Queuing Exponential Assumption vs. More Realistic Distribution of Examination Duration

Most realistic scenarios beyond these simple examples can become very complex, sometimes requiring sophisticated numerical methods or being mathematically intractable altogether. Simulation, conversely, can be used to accurately emulate large complex systems and interrelated subsystems which often cannot be effectively analyzed using other methods. According to Rising (1977), "before simulation models were available, there was no accurate way to estimate the relative size" of the impact of process changes. Simulation can accommodate any statistical distribution, can consider patient flow as dynamic over the course of a day (rather than as a steady state), and can incorporate more elaborate logic than above.

For example, Figure 3 shows the basic process by which patients flow through pediatrics. Upon arrival, patients check in with a receptionist and then wait in the waiting room. A medical assistant escorts each patient to an open exam room and preps the patient, who then waits for the primary provider. After the appointment is completed, a medical assistant cleans the exam room and prepares it for the next patient, who at this time can be brought in from the waiting room. One to three medical assistants work with a team of two to five providers, and a given number of exam rooms are available to each provider. Additionally, patients arrive randomly about their scheduled appointment times, and if more than a certain number of patients are waiting to be seen, a "float" RN may be utilized if available from

elsewhere in the facility or some patients may walk out. These types of scheduling particulars and conditional logic are usually impossible to incorporate into a queuing model but can be reasonably represented in a simulation program.

Table 3: Effect of Deviations in Exam Duration Variability from Exponential Assumption (M/G/1 queuing results)

Exam Duration		Average # Patients	Average Length of
Average	St. Dev.	Waiting	Wait
12 mins	0 mins	1.6 patients	24 mins
12 mins	3 mins	1.7 patients	26 mins
12 mins	6 mins	2.0 patients	30 mins
12 mins	9 mins	2.5 patients	38 mins
*12 mins	12 mins	3.2 patients	48 mins
12 mins	15 mins	4.1 patients	62 mins
12 mins	18 mins	5.2 patients	78 mins
12 mins	21 mins	6.5 patients	98 mins
12 mins	24 mins	8.0 patients	120 mins

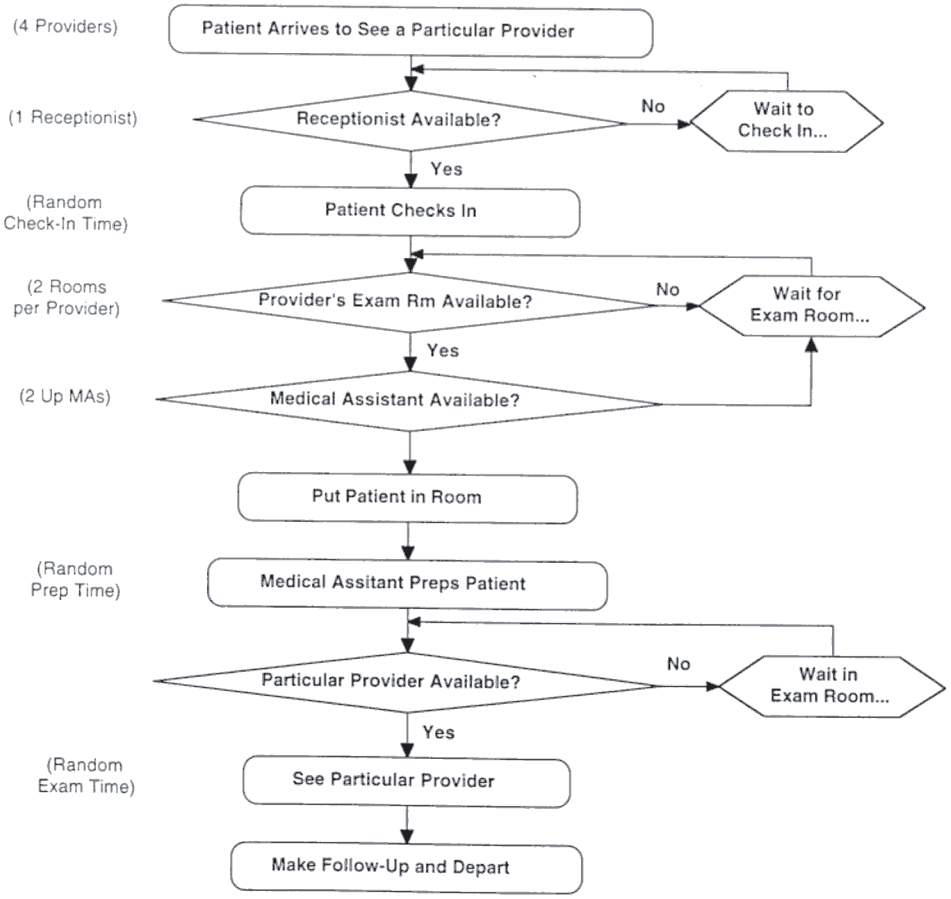

Figure 3: Patient Flow Through Pediatric Department

CONDUCTING A SIMULATION STUDY: PEDIATRIC PATIENT FLOW EXAMPLE

Figure 4 illustrates the general steps in a typical simulation study, and additional information can be found in Banks and Carson (1984, pp. 11-16). Note that these activities may be iterative and may not be strictly sequential. For example, knowledge of the specific analysis to be performed can influence model design and coding issues. Pallin and Kittel (1992) and Mahachek (1992) also discuss typical activities in healthcare simulation studies. In model development, the term *verification* refers to ensuring that the program is debugged and its logic performs as intended, while the term *validation* is the determination that the model accurately mimics the real process being studied. Although several techniques exist to perform these two steps, they remain as much an art as a science.

Simulation Inputs and Outputs

Table 4 lists the primary "inputs" in the pediatric model. In simulation terminology, some of these are referred to as *controllable variables* or *decision variables* because management can change them to impact process performance. Other variables are called *uncontrollable* if they are perceived to be beyond the scope of management control, such as patient timeliness. Analyses frequently still may be performed on these variables, however, such as for sensitivity analysis, robust design, and "imagineering" (e.g., "*What if* more patients arrived on time?").

Table 5 lists some of the "output" *performance measures* collected by the pediatric simulation. These data can be collected and analyzed overall and by type of staff, type of appointment, and time of day. Many other types of data are possible, with literally just about any conceivable statistic of interest being possible to simulate and analyze.

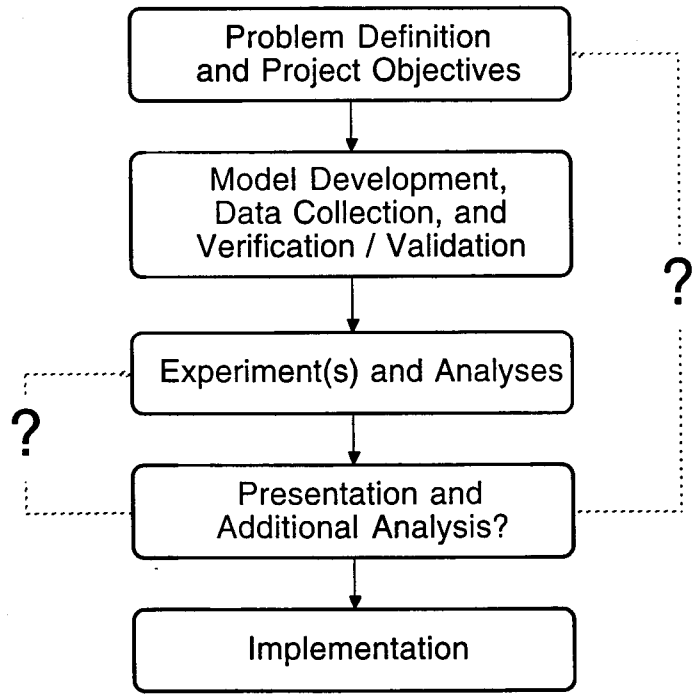

Figure 4: General Steps in a Simulation Study

Table 4: Process Decision Variables and Simulation "Inputs"

Number of:	Distribution of Time for:
• Receptionists	• Patient to Check-In
• Medical Assistants	• Medical Assistant to Prep Patient
• Pediatricians and Nurses	• Provider to Examine Patient (by type)
• Appointments per Provider	• Patient to Schedule Follow-Up
• Exam Rooms per Providers	• Medical Assistant to Clean Exam Room

Table 5: Simulation "Output" Performance Measures

Patient Waits:	Location and Number of Patients:
Total Patient Wait:	Waiting to Check-In
Wait for Receptionist	Checking-In
Wait to be Prepped:	In Waiting Room
Wait for Exam Room	Waiting for Exam Room
Wait for Medical Assistant	Waiting for Medical Assistant
Wait for Primary Provider	Being Prepped
Wait to Schedule Next Appointment	Waiting for Provider
Total Time Until Seen By Provider	Being Examined
	Waiting to Schedule Follow-Up
	Scheduling Follow-Up Appointment
Total Time in Pediatrics	
Resource Utilization:	Total Number of Patients:
Provider Idle Time and Utilization	Arrived
Medical Assistant Idle Time and Utilization	In Pediatric Department
Exam Room Utilization	Departed
Receptionist Idle Time and Utilization	

Model Development, Verification, and Validation

Development of the pediatric simulation started very simply in order to produce a working model, incrementally adding detail and debugging as each modification was made until sufficient sophistication existed for the intended analyses. The simulation program was thoroughly commented, documented, debugged, verified, and validated. Throughout this development phase, model performance was continually compared to the time study data and was reviewed with the CQI team, who commented on the accuracy of results. This iterative development process, although time-consuming, helped establish credibility with the client and trust in computer-generated analyses.

The final simulation model reasonably mimicked the actual pediatric department and accurately responded to recent staff changes. For example, Figure 5 compares simulated and actual average waits in each process step. Figure 6 shows the total number of simulated patients in the pediatric department and their location over a typical four hour session.

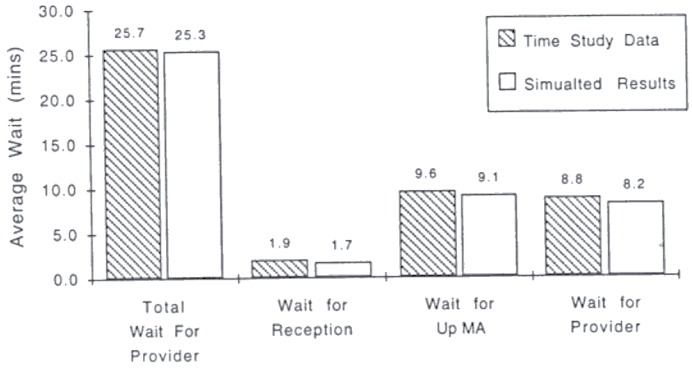

Figure 5: Comparison of Simulation Waiting Time Results to Real Process

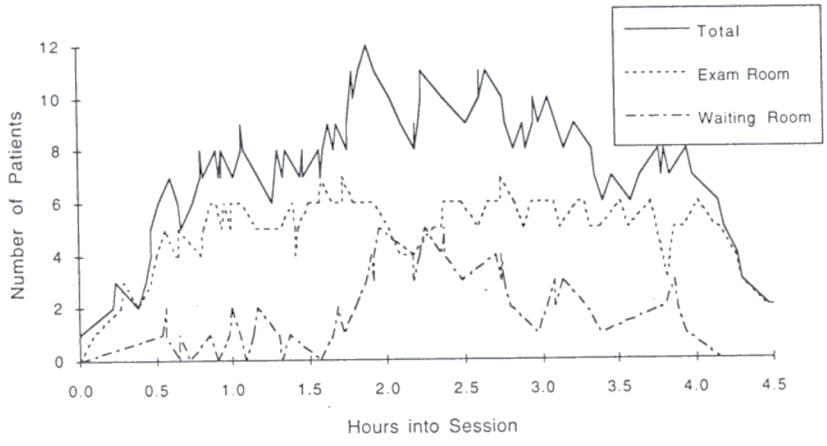

Figure 6: Simulated Location of Patients in Pediatrics

Similarly, Figure 7 shows the total time that all simulated patients waited over the course of this session, in aggregate and for each pediatrician. Many similar simulated sample paths

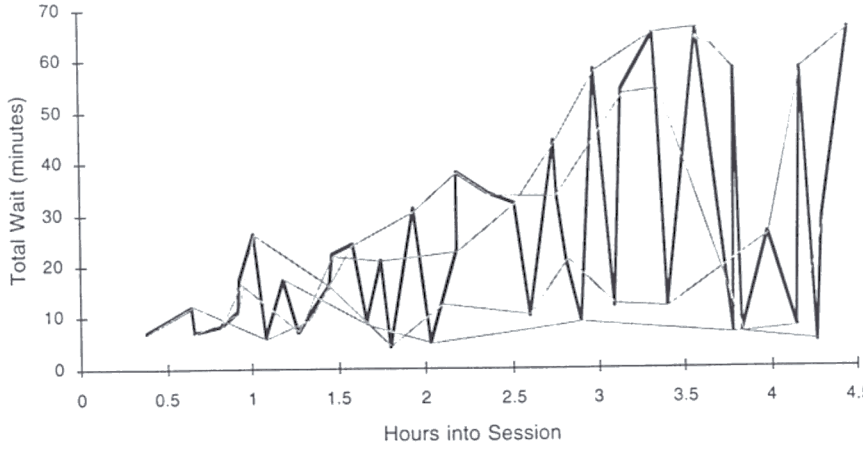

Figure 7: Simulated Patient Waits by Time of Day

suggest that the process tends to get backed up roughly half-way through each session, again agreeing with direct process observations. Upon viewing these figures, in fact, the medical director mistook them to depict time study data, commenting that this is precisely what happens everyday. (Process experts believing simulated data to be real data is one validation that the model performs reasonably true to life.) See Lowery and Martin (1992) for examples of other forms of model validation.

Analysis Results of Proposed Process Changes

Table 6 summarizes "*What If?*" ideas evaluated with the simulation. For example, Figures 8, 9, and 10 illustrate the simulated effect of the number of exam rooms, the number of medical assistants, and the volume of patients per provider, respectively. As these graphs indicate, reducing the volume of appointments per provider appears to have the largest single impact on patient waits, but at the expense of reduced provider utilization. Although more costly to implement, alternatively, little benefit is likely by adding only exam rooms or medical assistants. Based on this result, these costly low-impact decisions were avoided.

Table 6: Simulation Factors Examined for Impact on Member Waits

- Number of exam rooms available per provider.
- Provider-to-medical assistant staffing ratios.
- Volume of appointments booked per provider.
- Scheduling in "catch up" time at critical times of day.
- Redistributing certain types of appointments to more appropriate lengths.
- Additional full-time or part-time providers at particular times of day.
- Less variation in actual exam duration.
- Various combinations of the above.

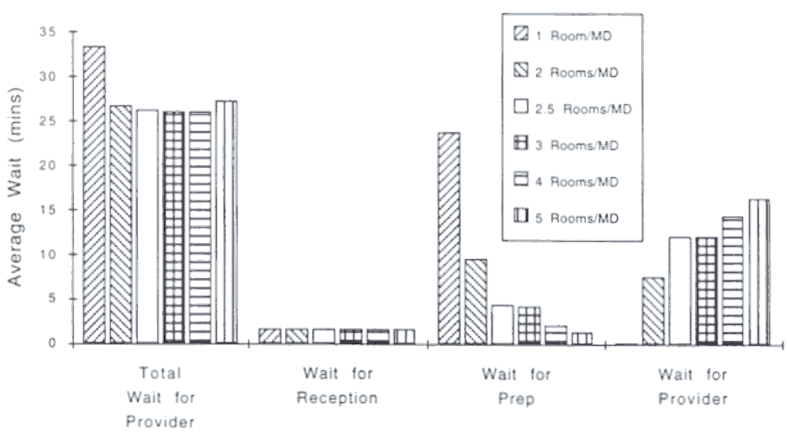

Figure 8: Simulated Effect of Number of Exam Rooms

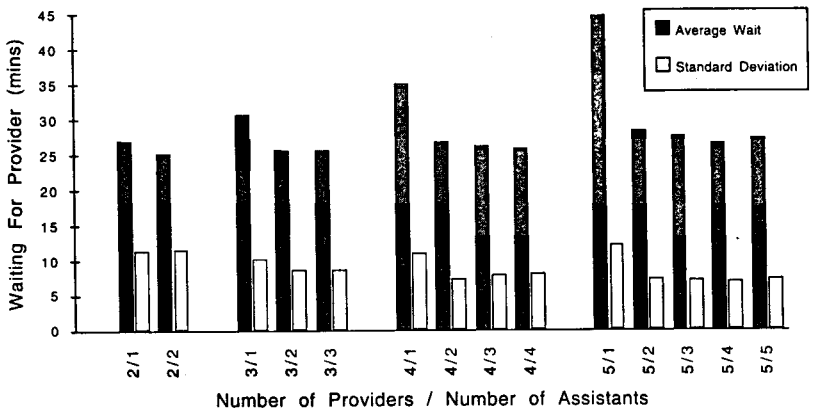

Figure 9: Simulated Effect of Number of Medical Assistants

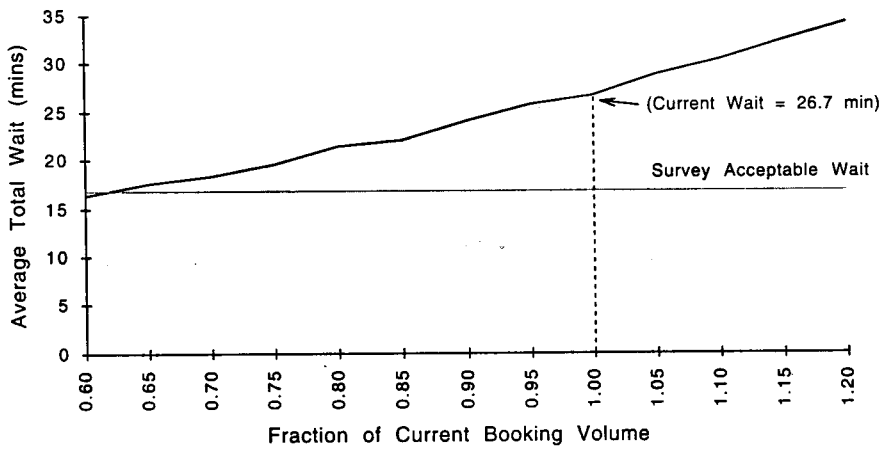

Figure 10: Simulated Effect of Number of Providers versus Patient Volume

Several combinations of additional exam rooms, additional pediatricians, and additional support staff therefore were identified for which simulated average waits met the 15 minute survey target, although management was reluctant to incur the considerable associated costs. Scheduling a floating RN with an additional exam room for the second half of each session, however, resulted in a 30% reduction in average waits. More general benefits of this study include a greater awareness of the fundamental tradeoff between patient waits and resource utilization.

ADDITIONAL CONSIDERATIONS FOR SUCCESSFUL SIMULATION STUDIES

Project Duration and Resources Required

Simulation can consume much more time than typically presumed. In fact, Keller, Harrell, and Leavy (1991) observed that many simulation projects take at least twice as long as originally estimated. Although this particular pediatric study was extensive, requiring 285 hours over a 4 month span, the relative expenditure of time to various activities, shown in Figure 11, agrees with figures reported by other authors. For example, to build the working simulation model,

22% of the effort went to programming, modeling, and debugging, with an additional 15% for validation and related statistical analysis. This experience is consistent with the observation by Law and McComas (1992) that "model coding represents only 30% to 40% of the total effort in a typical simulation study." Statistical analysis of results took 18% and meetings and administration took 16% of the total project effort. Of course, future similar studies which reuse or adapt the present model will take significantly less effort. For example, a few follow-up analyses for the pediatric department were provided in two to ten days.

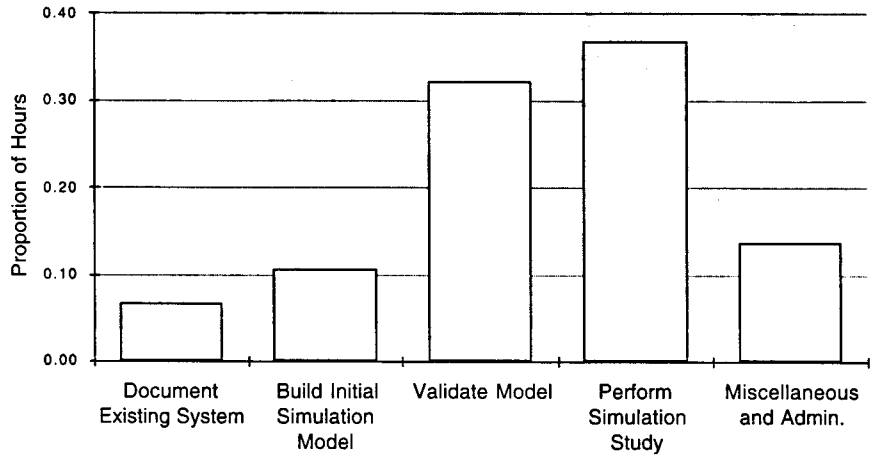

Figure 11: Distribution of Time in Pediatric Simulation Study

Technical Output Analysis

It almost goes without saying that statistically sound analysis of results is essential, often taking the form of some type of hypothesis test or experimental design. With software advances making computer simulation available to a larger mass of decision-makers, however, an increasing number of people are forming decisions without sufficient technical foundations. For example, erroneous conclusions often still are based on an insufficient number of replications (or even on only one execution!) of a simulation, sometimes encouraged by software gimmickry. These concerns are especially applicable to the growing field of animation, which has advanced to the point where the professional appearance of graphics easily can mislead non-simulationists about its validity for proper analyses, unknowingly misusing or misinterpreting results. As Shuman and Wolfe (1992) note:

> *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.*

Presentation of Results

Although not a "technical" issue, clear presentation of results, typically to administrators with less advanced statistical backgrounds, also is critical for fostering understanding and confidence in simulation analysis. For example, although more sophisticated experimental designs could have been performed earlier in the pediatric study, they potentially would have resulted in reduced management confidence. For these reasons, initial analyses were per-

formed "one-variable-at-a-time" (violating good experimental design principles) and portrayed graphically as simply as possible.

The Software Decision

The pediatric model was implemented in SIMAN, one of several popular simulation languages. Many other software packages are commercially available, with those that are easier to use generally not handling as much complexity, although the state of simulation software is rapidly changing. An advantage of all simulation programs is that they perform many standard simulation tasks which would otherwise require significant time and expertise to program completely from scratch. By transparently managing such technical considerations as the discrete event clock and event list, queue management, resource seizure, random variate generation, and data tracking, simulation languages free up an analyst's time and focus for other issues.

While cost and ease of use are important considerations, Law and McComas (1992) state that some software lacks sufficient flexibility for specific desired analysis. A good guideline, therefore, is to buy more capability than initially thought necessary. Additional criteria include modeling features, statistical capabilities, appropriate probability distributions, output processing capability, debugging and trace utilities, compatibility with third party add-ins, animation, and an ability to work at a programming level if desired and to compile with other code. Journals such as *Industrial Engineering*, *OR/MS Today*, and *Interfaces* periodically publish software reviews and provide vendor contact and cost information. For example, see Law and McComas (1989), Law and Haider (1989), and Banks *et al* (1991).

Finally, it is critical to emphasize that *simulation is not simply software.* (In fact, although very uncommon, simulation can be performed without using a computer at all.) While good software unquestionably is a major help, this does not relieve the user of the need to possess a solid understanding of random variation, sampling theory, sample paths, confidence intervals, experimental design, and differences between various probability distributions. Law and Haider (1989) also stress that "this knowledge is required regardless of the simulation package used," sometimes to a degree not provided in short seminars focused on a specific software product.

Some Other Pitfalls to Avoid

Pegden *et al* (1990) assert that "the quality of the analysis depends on the quality of the model and the skill of the modeler. Model building is an art, and, as such, the skill of practitioners varies widely." Keller, Harrell, and Leavy (1991) also emphasize that:

> *There are some serious misunderstandings concerning the nature of simulation and its ease of employment. The truth of the matter is that there's no such thing as "simple simulation." Its a myth often inadvertently perpetuated by manufacturers of simulation software and professors who want their students to believe they're learning an easier alternative to tools like linear programming.*

Additional concerns are discussed by Banks and Carson (1989) and Law and McComas (1989), including:

- Unclear problem statement and objective;
- Not involving the decision-makers throughout the study;
- Not accurately understanding the process being studied;
- Not capturing appropriate process dependencies and relationships;
- Inappropriate level of detail (either too much or too little);

- Not accurately capturing randomness in system;
- Not taking time to collect process data and identify appropriate probability distributions;
- Use of means, when variability and distributions are important;
- Misuse of animation; and
- Lack of verification and validation.

CONCLUSION

The pediatric project demonstrated the usefulness of computer simulation for exploring tradeoffs between patients waits, resource utilization, and costs. Similar approaches can be taken in other departments and towards other concerns, including appointment access, scheduling methods, telephone access, and policy and resource planning. For example, an insight gained through the pediatric study was that additional exam rooms and support staff would have only marginal benefit without additional pediatric sessions. Consequently, use of simulation with experimental design, robust design, and meta-modeling (see Box, Hunter, and Hunter, 1982) are being explored in order to develop predictive equations and to recommend changes to corporate standards regarding staff levels and panel sizes. More recently, simulation has been used to study and improve the quality of clinical laboratories, such as the diagnostic accuracy of Pap smear, mammogram, HIV, and hepatitis results.

REFERENCES

Banks, J. and Carson, J. S. 1984. *Discrete-Event System Simulation*, Englewood Cliffs, NJ: Prentice-Hall, Inc.

Banks, J., Aviles, E., McLaughlin, J. R., and Yuan, R. C. 1991. "The Simulator: New Member of the Simulation Family," *Interfaces*, Vol. 21, No. 2, pp. 76-86.

Benneyan, J. C., Horowitz, M. I., and Terceiro, M. B. 1994. "Using Computer Simulation to Help Reduce Patient Waits," *Proceedings of the Healthcare Information and Management Systems Society*, Vol. 1, pp. 323-342.

Box, G. E. P., Hunter, W. G., and Hunter, J. S. 1978. *Statistics for Experimenters*, New York: Wiley.

Fetter, R. B. and Thompson, J. D. 1966. "Patients' Waiting Time and Doctors' Idle Time in an Outpatient Setting," *Health Services Research*, Vol. 1, p 66.

Fries, B. E. 1976. "Bibliography of Operations Research in Health-Care Systems," *Operations Research*, Vol. 24, No. 5, pp. 801-814.

Giglio, R. J., ed. 1992. *Journal of the Society for Health Systems, Issue Focus: Simulation*, Vol. 3, No. 3.

Keller, L., Harrell, C., and Leavy, J. 1991. "The Three Best Reasons Why Simulation Fails," *Industrial Engineering*, pp. 27-31, April 1991.

Law, A. M. and Haider, S. W. 1989. "Selecting Simulation Software for Manufacturing Applications: Practical Guidelines and Software Survey," *Industrial Engineering*, May 1989, pp. 33-46.

Law, A. M. and Kelton, W. D. 1991. *Simulation Modeling and Analysis*, second edition, New York: McGraw-Hill, Inc.

Law, A. M. and McComas, M. G. 1989. "Pitfalls to Avoid in the Simulation of Manufacturing Systems," *Industrial Engineering*, May 1989, pp. 28-32.

Law, A. M. and McComas, M. G. 1992. "How to Select Simulation Software for Manufacturing Applications," *Industrial Engineering*, July 1992, pp. 29-35.

Lowery, J. C. and Martin, J. B. 1992. "Design and Validation of a Critical Care Simulation Model," *Journal of the Society for Health Systems*, Vol. 3, No. 3, pp. 15-36.

Mahachek, A. R. 1992. "An Introduction to Patient Flow Simulation for Health-Care Managers," *Journal of the Society for Health Systems*, Vol. 3, No. 3, pp. 73-81.

Nuffield Report 1965. *Waiting in Hospital Outpatient Departments*, Oxford, England: Oxford University Press.

Pallin, A. and Kittel, R. P. 1992. "Mercy Hospital: Simulation Techniques For ER Processes," *Industrial Engineering*, Feb. 1992, pp. 35-37.

Pegden, C. D., Shannon, R. E., and Sadowski, R. P. 1990. *Introduction to Simulation Using* SIMAN, New York: McGraw-Hill, Inc.

Pierskalla, W. P. and Urban, G. L., eds. 1976. *Operations Research, Special Issue on Healthcare*, Vol. 24, No. 5, Sept.-Oct. 1976.

Pritsker, A. 1992. "Simulation: The Premier Technique of Industrial Engineering," *Industrial Engineering*, July 1992, pp. 25-26.

Rising, E. J. Baron, R., and Averill, B. 1973. "A Systems Analysis of a University Health Service Outpatient Clinic," *Operations Research*, Vol. 21, No. 5, pp. 1030-1047.

Rising, E. J. 1977. *Ambulatory Care Systems, Volume 1: Design for Improved Patient Flow*, Lexington, MA: Lexington Books.

Roberts, S. D. and England, W. L., eds. 1981. *Survey of the Application of Simulation to Healthcare*, Simulation Series, Vol. 10, No. 1, La Jolla, CA: The Society for Computer Simulation.

Shuman, L. J. and Wolfe, H. 1992. "Introduction," *Journal of the Society for Health Systems*, Vol. 3, No. 3, pp. 2-4.

Wilt, A. and Goddin, D. 1989. "Healthcare Case Study: Simulating Staffing Needs and Work Flow in an Outpatient Diagnostic Center," *Industrial Engineering*, May 1989, pp. 22-26.

Wolff, R. 1989. *Stochastic Modeling and the Theory of Queues*, Englewood Cliffs, NJ: Prentice Hall, Inc.

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