Chapter 8

DISCRETE-EVENT SIMULATION OF HEALTH CARE SYSTEMS

Sheldon H. Jacobson[1], Shane N. Hall[2] and James R. Swisher[3]
[1,2]*Department of Mechanical and Industrial Engineering, 1206 West Green Street (MC-244), University of Illinois at Urbana-Champaign, Urbana, IL 61801-2906*
[3]*Mary Washington Hospital, 1001 Sam Perry Boulevard, Fredericksburg, VA 22401*

Abstract: Over the past forty years, health care organizations have faced ever-increasing pressures to deliver quality care while facing rising costs, lower reimbursements, and new regulatory demands. Discrete-event simulation has become a popular and effective decision-making tool for the optimal allocation of scarce health care resources to improve patient flow, while minimizing health care delivery costs and increasing patient satisfaction. The proliferation of increasingly sophisticated discrete-event simulation software packages has resulted in a large number of new application opportunities, including more complex implementations. In addition, combined optimization and simulation tools allow decision-makers to quickly determine optimal system configurations, even for complex integrated facilities. This chapter provides an overview of discrete-event simulation modeling applications to health care clinics and integrated health care systems (e.g. hospitals, outpatient clinics, emergency departments, and pharmacies) over the past forty years.

Key words: discrete-event simulation, health care services, hospitals, clinics

Acknowledgements: The authors wish to thank Dr. R.W. Hall for his comments and feedback on an earlier draft of this chapter, resulting in a significantly improved final version. The first author has been supported in part by the National Science Foundation (DMI-0222597, DMI-0457176).

1. INTRODUCTION

Over the past 40 years, escalating health care costs have provided researchers and health care professionals with the impetus to identify new approaches to improve the efficiency of health care operations and to reduce delivery costs. Discrete-event simulation has become a popular tool for health care decision-makers to support their efforts in achieving these objectives. Discrete-event simulation is an operations research modeling and analysis methodology that permits end-users (such as hospital administrators or clinic managers) to evaluate the efficiency of existing health care delivery systems, to ask "what if?" questions, and to design new health care delivery system operations. Discrete-event simulation can also be used as a forecasting tool to assess the potential impact of changes on patient flow, to examine asset allocation needs (such as in staffing levels or in physical capacity), and/or to investigate the complex relationships among different system variables (such as the rate of patient arrivals or the rate of patient service delivery). Such information allows health care administrators and analysts to identify management alternatives that can be used to reconfigure existing health care systems, to improve system performance or design, and/or to plan new systems, without altering the existing system.

The application of discrete-event simulation in the analysis of health care systems has become increasingly more accepted by health care decision-makers as a viable tool for improving operations and reducing costs. This is due in part to the large number of successful discrete-event simulation health care studies reported in the literature, as well as ongoing enhancements to simulation software packages that make their application to health care less arduous. This chapter surveys the large body of discrete-event simulation modeling and analysis efforts that have been reported to address health care delivery system problems and provides an up-to-date, comprehensive collection of articles describing these applications.

This chapter focuses on articles that analyze single or multi-facility health care clinics, including outpatient clinics, emergency departments, surgical centers, orthopedics departments, and pharmacies. An extensive taxonomy of the literature over the past 30 years is presented (though some relevant earlier articles are also referenced). Discrete-event simulation studies on wide area or regional health care community planning, ambulance location service, gurney transportation, disease control planning, and studies that do not address some aspect of patient flow are not discussed. For a complete review of the literature in health care prior to the mid-1970s, see England and Roberts (1978) and Valinsky (1975).

Several excellent review articles have appeared that examine conducting a discrete-event simulation study in health care clinics. England and Roberts (1978) provide a thorough and comprehensive survey on the application of discrete-event simulation in 21 health care settings (including laboratory studies, emergency services, and the national health care system). Their detailed survey cites 92 discrete-event simulation models out of 1,200 models reviewed, including all published models through 1978. Klein et al. (1993) present a bibliography that includes operational decision making, medical decision making, and system dynamics planning models. Smith-Daniels et al. (1988) present a literature review pertaining to acquisition decisions (e.g., facility location, aggregate capacity, and facility sizing) and allocation decisions (e.g., inpatient admissions scheduling, surgical facility scheduling, and ambulatory care scheduling), including several operations research methodologies, such as heuristics, Markov chains, linear programming, and queuing theory, as well as discrete-event simulation. Jun et al. (1999) present a survey of discrete-event simulation applications to clinic design and analysis. Note that this chapter builds upon the Jun et al. survey and provides new updates that have been reported since 1999.

2. FUNDAMENTALS OF DISCRETE-EVENT SIMULATION IN HEALTH CARE

An important advantage of using discrete-event simulation, over other modeling techniques like linear programming or Markov chain analysis, when modeling a health care clinic is the capacity to model complex patient flows through health care clinics, and to play "what if" games by changing the patient flow rules and policies. The success or failure of a discrete-event simulation study within a health care environment often depends on a standard sequence of carefully followed steps. Law and Kelton (2001) outline the key steps necessary to undertake a successful simulation study. These steps include the formulation of the problem and the plan of study, the collection of data and the conceptual model design, the validation of the model, the constructions of the computer representation of the model, the verification of the model, the design of experiments needed to address the problem being studied, production runs using the computer model, the statistical analysis of the data obtained from the production runs, and the interpretation of the results with respect to the system under study. Eldabi and Paul (2001) notes that a key issue in the success of health care simulation studies is the careful formulation of the problem statement, and the buy-in of all stakeholders. In manufacturing simulation studies, modeling and data errors may lead to unexpected costs and poor

performance. However, in health care simulation studies, such errors can ultimately lead to lives lost and the associated liabilities surrounding such events. Therefore, the tolerable margin for error in the design and application of health care simulation models is significantly more limited. Such restrictions provide obstacles and barriers that can only be overcome through the highest attention to detail and accuracy, as well as fluid communization between all stakeholders.

The additional references that follow address the fundamental principles for performing a discrete-event simulation study of a healthcare system. These are excellent references that provide detailed methodologies for a successful simulation study in the context of healthcare. Hence, for brevity, these methodologies are omitted here. Banks and Carson (1987) and Mahachek (1992) provide structured tutorials on the steps that should be followed when conducting a health care system discrete-event simulation study. Mahachek (1992) also provides details of a discrete-event simulation study on hospital patient flow. Kanon (1974) shows how one could use sample data to build a discrete-event simulation model of a simplified problem in a hospital setting. Eldabi and Paul (2001) discuss an iterative approach to modeling health care systems, while Harper (2002) and Vissers (1998) discuss the general framework and process for operational modeling in heath care. Isken et al. (1999) present a general simulation modeling framework for outpatient obstetrical clinics that is applicable to other types of outpatient clinics. Finally, Morrison and Bird (2003) detail a simulation methodology for improving patient care in ambulatory heath care.

Lowery (1998, 1996) and Standridge (1999) discuss issues facing an analyst when using discrete-event simulation to study a health care system, such as what type of problems are appropriate to be addressed using simulation, the degree of model complexity, the definition of input distributions, model documentation and validation, and the interpretation and reporting of findings. Sanchez et al. (2000) discuss other emerging issues that affect a successful health care discrete-event simulation study, such as the expansion of information technology and the combining of information technology with traditional process models. Baldwin et al. (2004) discuss an iterative approach to health care simulation modeling that is meant to increase the understanding of the problem to decision-makers and enhance communication between stakeholders of the health care system that is being modeled. All of these articles provide useful information for practitioners interested in using discrete-event simulation to study health care systems and issues. Moreover, these articles stress the ability of discrete-event simulation to aptly address the unique factors inherent to health care systems.

Discrete-event simulation models that have been used to analyze health care delivery systems have primarily focused in two areas: (1) optimization and analysis of patient flow and (2) allocation of assets to improve the delivery of services. The first area considers patient flow through hospitals and clinics, with the primary objective of identifying efficiencies that can be realized to improve patient throughput, reduce patient waiting times, and improve medical staff utilization. The second area considers the number of beds and staffing requirements necessary to provide efficient and effective health care services. This section reviews the breadth of studies and approaches taken in these two distinct, though related, areas.

2.1 Patient Flow Optimization and Analysis

As hospitals and clinics face ongoing competition for their services, they must be able to provide fast and efficient health care in order to attract new patients and retain their existing patients. High quality, efficient patient flow is a function of high volume patient throughput, low patient waiting times, short total visit times, and low levels of staff overtime coupled with the maintenance of reasonable staff utilization rates and low physician idle times. Three areas that have a significant impact on patient flow are patient scheduling and admissions, patient routing and flow schemes, and appointment scheduling and availability of resources.

2.1.1 Outpatient Scheduling

Outpatient scheduling focus on procedures for setting the timetable to match patients with caregivers, both in terms of when these appointments are set and their length of time. This involves rules or policies that determine when appointments can be made (such as morning versus afternoon) and the length of time (or spacing) between appointments. This may also include the specific types of caregiver who will be responsible for treating patients and the physical space that will be required to deliver the necessary care and treatment. All these issues have a significant impact on how health care personnel and facility resources can be optimally used such that patient flow is maximized without incurring additional costs or excessive patient waiting.

The majority of discrete-event simulation studies that focus on patient scheduling and admissions are focused on outpatient clinics. Guo et al. (2004) outline a simulation framework for analyzing scheduling rules for outpatient clinics. This framework, termed Patient Scheduling Simulation Model (PSSM), addresses four key components of an outpatient clinic scheduling system: demand for appointments, supply of physician time blocks, patient flow, and the scheduling algorithm. The study provides a

demonstration of the framework for a pediatric ophthalmology clinic and discusses some challenges for adapting the framework to other settings. Outpatient clinics typically schedule appointments over some future time horizon. A discrete-event simulation study of rolling horizon appointment scheduling is presented by Rohleder and Klassen (2002). This study considers two common management policies: Overload Rules and Rule Delay. The Overload Rules policy considers scheduling methods such as overtime and double booking that are used when demand is high, while the Rule Delay policy determines when to implement Overload Rules. The authors conclude that determining the "best" scheduling policy depends on the measures of performances that are deemed most important by decision-makers.

Fetter and Thompson (1965) present one of the earliest discrete-event simulation studies conducted in the area of individual clinical facility operations for outpatient clinics. They analyze physician utilization rates with respect to patient waiting time by using different input variables (such as patient load, patient early or late arrival patterns, no-show rates, walk-in rates, appointment scheduling intervals, physician service times, interruptions, and physician lunch and coffee breaks). They concluded that if the physician appointment load increases from 60% to 90% (capacity), the physician idle time decreases by 160 hours and patient waiting time increases by 1600 hours (cumulative over a fifty day period). With such a capacity increase, they suggest that the physician's time would have to be worth ten times the patient's time to justify such a shift in patient scheduling and admission policies.

Smoothing the distribution of patient demand has been used to improve patient throughput and patient waiting times in outpatient clinics. Smith and Warner (1971) compare patients arriving according to a uniformly scheduled arrival pattern versus patients arriving in a highly variable manner. They show that the uniformly scheduled arrival pattern can decrease the average length of stay at the clinic by over 40% (from 40.6 minutes to 24 minutes), due to the more predictable use of resources when patient arrivals are uniformly spaced. Similarly, Rising et al. (1973) show that increasing the number of appointments slots in an outpatient clinic on those days that had the least number of walk-ins smoothed the demand on the physician, resulting in a 13.4% increase in patient throughput and less clinic overtime. Kho and Johnson (1976) and Kachhal et al. (1981) show that in a radiology department and in an ear, nose, and throat clinic, respectively, performance can be improved when demand for outpatient services is evenly distributed.

In contrast to uniform scheduling, a number of alternative scheduling rules have been studied. Bailey (1952) studies an outpatient clinic

scheduling rule (where two patients are scheduled at the beginning of every session, morning or afternoon, with all other patients scheduled at equal intervals) that yields acceptable results for both patients (in terms of waiting times) and staff (in terms of utilization), assuming that all patients have the same service time distributions and that all patients arrive at their designated times. Smith et al. (1979) use a modified-wave scheduling scheme (where more patients are scheduled at the beginning of each hour and less towards the end of the hour, thus allowing the physician to absorb unexpected delays and return back to schedule at the end of each hour) for an outpatient clinic to find the maximum number of patients a physician could see while minimizing patient waiting time. They show that this schedule is superior to the uniform scheduling scheme, in terms of patient flow and patient waiting times. Williams et al. (1967) study the relationship between physician utilization and patient waiting time in an outpatient clinic using a staggered block scheduling system (i.e., eight patients arriving every half hour) versus the single block scheduling system (i.e., sixteen patients arriving simultaneously). The single block system emphasizes the physician's idle time, while the staggered block system emphasizes the patient's waiting time, resulting in a substantial decrease in the patient waiting times (with no decrement in the utilization of the physician).

2.1.2 Inpatient Scheduling and Admissions

Inpatient scheduling and admissions focus on procedures for matching patients with caregivers (e.g., surgeons, infectious disease specialists) within a hospital or similar health care facility. This involves rules or policies that determine when healthcare providers must see and provide services for inpatients, as well as matching specific types of caregiver with the needs of patients and the necessary treatments.

Surgical (operating room) center scheduling has also been studied using discrete-event simulation. Magerlein and Martin (1976) review the literature on using discrete-event simulation for scheduling surgical centers. Murphy and Sigal (1985) examine surgical block scheduling, where a block of operating room time is reserved for one or more surgeons. Fitzpatrick et al. (1993) study the use of first-come-first-serve, fixed (scheduling the same block of time in the same time slot each day of the week), variable (scheduling under the influence of seasonal fluctuation in demand), and mixed block scheduling (a combination of fixed and variable) for hospital operating rooms. They observed that variable block scheduling is superior to all scheduling policies, in terms of facility utilization, patient throughput, average patient waiting time, and patient queue length.

Klassen and Rohleder (1996) use discrete-event simulation to study the best time to schedule patients with large patient service time means and variances. They analyze several rules and arrive at the best result (which is to schedule such patients towards the end of the appointment session) that minimizes the patient's waiting time and the physician's idle time. Additionally, they analyze the best position for unscheduled appointment slots for potentially urgent calls and found no conclusive scheduling rule. Swisher et al. (1997) consider scheduling more patients with larger mean service time distributions in the morning session, rather than the afternoon, in an outpatient clinic. They found that staff overtime is sharply reduced, with a corresponding reduction in the physician's lunch time period. Steward and Standridge (1996) report the results of an overtime study using a discrete-event simulation model of a veterinary practice. The veterinary domain is very similar to the larger human medical systems domain, since both involve the challenge of varying flow and service rates, as well as resource utilization, staffing, demand, and scheduling. In this study, the performance measure of interest is the average time interval between the closing time of the clinic and the time the last client is discharged after clinic hours, which serves as an indicator of overhead cost and client satisfaction. They report that performance can improve if the clinic disallows the scheduling of appointments less than 90 or 120 minutes prior to closing, rather than 60 minutes, as was the current practice.

Hancock and Walter (1979) attempt to use discrete-event simulation to reduce the variance in occupancy levels in a hospital inpatient facility, with the goal of increasing patient throughput and maximizing average occupancies. Unfortunately, they were unsuccessful in achieving their stated objective, since the staff was accustomed to admitting patients on the date of the requests 90% of the time, and they refused to schedule over four weeks in advance. Hancock and Walter (1984) attempt to smooth the daily patient loads of nineteen hospital departments by varying the admission days of urgent inpatient and outpatient loads. The variation in average load for each of the departments suggested that no one single admission policy could provide a stable workload for all the departments, since each department had its own unique patient arrival patterns and treatment requirements, including different inpatient and outpatient requirements.

Lim et al. (1975) apply two admission policies (quickcall and maximum queue lengths) to a discrete-event simulation model of an inpatient orthopedics unit. "Quickcall" is defined as a patient willing to enter the hospital on very short notice; whereas, maximum queue lengths is a concept in which the physicians are required to maintain a maximum number of patient requests on a waiting list. Both systems improved system

performance, in terms of patient waiting times and staff utilization. Similarly, Groothuis et al. (2001) investigate two patient scheduling procedures (the current procedure where no patient is scheduled after 4:00 PM, versus scheduling a fixed number of patients each day) for a hospital cardiac catheterization lab. Both scheduling procedures were applied to the current configuration and three additional experimental configurations, with patient throughput and working day duration as the measures of performance. A discrete-event simulation was designed using Medmodel and showed that the third experimental configuration under the current scheduling procedure could, on average, accommodate two additional patients with fewer working days that exceed eight hours.

Walter (1973) describes several aspects of a queuing system in a radiology department, using several different appointment schemes. By segregating patients into inpatient and outpatient sessions with a similar examination time distribution, Walter observed that a substantial staff time savings was possible. He also found that the practice of giving multiple bookings for a given appointment time (i.e., overbooking) yields a small increase in staff utilization while substantially increasing the patient waiting time, and that efficiency always improves when the proportion of patients with appointments increases, resulting in a smoothing of the arrival rate. Goitein (1990) obtained similar conclusions using Monte Carlo simulation to examine factors such as physician idle time relative to patient waiting time. He found that if the physician overbooked the schedule (even slightly), patients would experience very long waiting times. His model provides insights into how delays build up as a result of commonly-observed statistical fluctuations. Everett (2002) suggests using a simulation model to help match patient needs with hospital availability (in a public hospital system) by scheduling patients waiting for elective surgery.

In conclusion, patient scheduling and admission rules along with patient appointment timing can have significant impacts on physician utilization and patient waiting. In general, studies using discrete-event simulation as discussed here suggest that rules and policies can be employed that will help to balance the tradeoff between physician utilization rates and patient waiting times, though the unique features of each clinic environment need to be taken into account to determine the exact extent of these tradeoffs. External market factors often dictate how health care facilities must prioritize the tradeoff between patient convenience and caregiver utilization. For example, in highly competitive markets, clinics may favor patient convenience over staff utilization in an effort to retain market share. Obviously, the unique factors that determine optimality must be elicited from each decision-maker given his/her environmental factors. The studies presented herein also point to the importance of, when possible, smoothing

patient arrival rates and service times. As in most systems, reducing variability facilitates performance improvement.

2.1.3 Emergency Room Simulation Models

Discrete-event simulation models can capture complex patient flows through health care clinics, as well as analyze the effect of new patient flow rules and policies. Such flows are typical in emergency room settings, where patients arrive (nearly always without appointments), and require treatment over a large and varied set of ailments and conditions, ranging from the benign (e.g., mild sports injuries) to the fatal (e.g., heart attacks, gunshot wounds). Although the patient arrival patterns are highly unpredictable, the treatment sequence can be controlled by clinical staff. Therefore, by altering patient routing and flow, it may be possible to minimize patient waiting times and increase staff utilization rates.

Limited access to primary care has led to extreme increases in emergency department usage across the United States. Emergency department overcrowding has been recognized by national health industry groups and regulatory bodies like the American Hospital Association (AHA) and the Joint Commission on the Accreditation of Healthcare Organizations (JCAHO) as a significant public health issue. All of this has led to a significant increase in the use of discrete-event simulation in modeling emergency departments in the past decade. General guidelines for analyzing an emergency department using discrete-event simulation exist in the literature. Takakuwa and Shiozaki (2004) propose a procedure for planning emergency room operations that minimize patient waiting times. Sinreich and Marmor (2004) develop a general emergency department simulation tool that is "flexible, intuitive, simple to use and contains default values for most of the system's parameters." Miller et al. (2004) describe steps for building a discrete-event simulation tool meant to determine the best emergency room configuration.

A key service metric used by hospital emergency departments is patient waiting time. Garcia et al. (1995) analyze the impact of a fast track queue on reducing waiting times of low priority patients in an emergency room. Emergency room patients are typically prioritized according to patient acuity (the level of sickness), hence low acuity patients regularly wait for excessively long periods of time. A fast track queue is used to treat a particular patient acuity level (in this case, non-urgent patients). They found that a fast track lane that uses a minimal amount of resources could result in significantly reduced patient waiting times. A similar study to assess the effect of fast care processing routes for non-critical patients on waiting times

in an emergency department is presented by Mahapatra et al. (2003). This study showed that the addition of an alternate care unit (such as a fast track unit) improved average waiting times by at least 10%. In a discrete-event simulation model of the emergency department at the University of Louisville Hospital, Kraitsik and Bossmeyer (1993) suggest that patient throughput can be improved using a fast track queue and a "stat" lab for processing high volume tests. Kirtland et al. (1995) examine eleven alternatives to improve patient flow in an emergency department and identified three alternatives (using a fast track lane in minor care, placing patients in the treatment area instead of sending them back to the waiting room, and the use of point-of-care lab testing) that can save on average thirty eight minutes of waiting time per patient. Blake and Carter (1996) also analyze an emergency department at the Children's Hospital of Eastern Ontario using discrete-event simulation. Their study led to the implementation of a fast track queue for treating patients with minor injuries.

Another important measure for emergency department efficiency is the overall time a patient spends in the emergency room (i.e., the patient length of stay). McGuire (1994) uses MedModel to determine how to reduce the length of stay for patients in an emergency service department in a SunHealth Alliance hospital. The results from the study resulted in several alternative recommendations, including adding an additional clerk during peak hours, adding a holding area for waiting patients, extending the hours of the fast track queue, and using physicians instead of residents in the fast track area. Miller et al. (2003) use a discrete-event simulation of an emergency department of a large hospital in the southeast United States to show that significant process changes would be required to meet specified goals for patient length of stay. Samaha et al. (2003) describe how discrete-event simulation was used by the Cooper University Hospital to reduce patient length of stays in their emergency department. Their study determined that length of stay was a process related problem rather than resource dependent. For example, the study showed that adding square footage or beds would not shorten the length of stay, which resulted in significant cost avoidance. Another discrete-event simulation study of patient flow to reduce emergency department length of stay is presented by Blasak et al. (2003). This study also simulates an inpatient medical telemetry unit to see how the processes of other units impact the emergency department. El-Darzi et al. (1998) and Martin et al. (2003) present additional patient flow simulation studies that seek to increase patient throughput and decrease patient length of stay. Both studies, however, model a hospital geriatric department.

Ritondo and Freedman (1993) show that changing a procedural policy (of ordering tests while in triage) results in a decrease in patient waiting times in

the emergency room and an increase in patient throughput. Edwards et al. (1994) compare the results of simulation studies in two medical clinics that use different queuing systems: serial processing, where patients wait in a single queue, and quasi-parallel processing, where patients are directed to the shortest queue to maintain flow. They show that patient waiting times could be reduced by up to 30% using quasi-parallel processing. Johnson (1998) uses a MedModel discrete-event simulation model to examine the effect of new legislation (requiring a minimum length of stay) and physician practices on patient flow and census of the maternity unit at Miami Valley Hospital in Dayton, Ohio, USA. The study led to minor changes in the maternity unit configuration that resulted in a 15-20% increase in patient volume and more balanced utilization of all areas within the unit. Also, the model results supported decisions to construct new facilities, such as a larger perinatal intensive care unit.

2.1.4 Specialist Clinics

Specialists bring their own unique set of issues when scheduling patients and allocating space within health care facilities. Sepúlveda et al. (1999) use discrete-event simulation to evaluate improvement in patient flow at a cancer treatment center under three different scenarios: 1) a change in the layout of the clinic, 2) different patient scheduling options, and 3) a new facility with increased capacity. The simulation of all three scenarios identified key patient flow bottlenecks and provided insights to improve patient flow and utilization. In particular, under the layout scenario, the simulation was used to identify a facility layout that allowed for a 100% increase in chair capacity. Simulating different patient scheduling options showed a 20% increase in the number of patients seen per day, without any change in the operating time of the treatment center. Finally, the new facility scenario showed that one of the waiting rooms did not have the capacity to support patient flow.

Ramakrishnan et al. (2004) describe a discrete-event simulation model used to analyze different "what-if" scenarios for the Wilson Memorial Regional Medical Center in Broome County, New York USA. The center recently implemented a digital image archiving system within its radiology services department and with this implementation wanted to identify patient flow changes in the computerized tomography (CT) scan area that would maximize patient throughput and minimize report generation time. Using simulation, the researchers identified changes within the CT scan area that would increase patient throughput by 20%, while simultaneously reducing report generation time by over 30%. Likewise, Alexopoulos et al. (2001)

describe a discrete-event simulation used by Partnership of Immunization Providers to study "what-if" scenarios for immunization clinics serving the poor. Such scenarios included narrowing/expanding appointment slots and the impact of bilingual versus monolingual staff on patient throughput.

Groothius et al. (2002) describe a systematic approach for analyzing the effects on patient flow when a hospital department is relocated. This approach is demonstrated with a MedModel simulation model of relocating a hospital phlebotomy department, which assesses the resulting impact on the average patient turn around time. They observed that this time could be reduced by as much as 50% (from 12 minutes down to 8 minutes).

2.1.5 Physician and Health Care Staff Scheduling

The majority of discrete-event simulation models for scheduling health care clinics are directed at patient scheduling (so as to optimally distribute patient demand to physicians and clinical staff). A number of studies, however, have addressed the reverse problem; namely, scheduling physician and clinical staff to satisfy patient demand, given a collection of patient arrivals. For example, walk-in clinics, which are unable to control the arrival rate of patients, must schedule their staff accordingly. Incorporating this idea, Alessandra et al. (1978) study both the staffing levels and patient arrival rates to ease bottlenecks and to improve patient throughput. Eight alternatives that varied the staffing pattern and the patient scheduling scheme were analyzed. The best alternative identified was to keep the staffing and arrival rate the same, but to distribute the current morning appointment patients to the afternoon shift. Mukherjee (1991) identifies a staffing mix that reduces patient waiting time and increases patient throughput, while controlling resource costs in a pharmacy.

There have also been discrete-event simulation studies that address physician scheduling. Rossetti et al. (1999) use discrete-event simulation to test alternative physician-staffing schedules at the emergency department at the University of Virginia Medical Center. For each staffing alternative, they analyzed the impact on patient throughput and resource utilization. Tan et al. (2002) present a discrete-event simulation study of an urgent care center that simulates the current physician schedule and a proposed schedule to test if the proposed schedule reduces the average total time patients spend at the facility. The simulation showed an 18% reduction in total visit time using the proposed schedule. Likewise, using a discrete-event simulation, Lach and Vázquez (2004) study a telemedicine program in Mexico that provides medical assistance to those living in extreme poverty. This study analyzes the effect on patient throughput and resource (tele-consult) utilization when an extra physician is scheduled; both tele-consult utilization

and patient throughput increase when the extra physician is scheduled. Osidach and Fu (2003) study the staffing of technicians required to perform medical exams on scheduled survey participants in a mobile examination center. Configurations of three, four, and five technicians for a batch arrival of seven survey participants were simulated to minimize the technicians' idle time and average time spent in the system by the survey participant. The best configuration for utilization was a three technician configuration, whereas a five technician configuration was the most time-effective; however, the five technician configuration also resulted in an overly crowded examination center.

Several discrete-event simulation models of nursing staff scheduling in emergency departments have been developed. Emergency room staff scheduling has its own unique challenges, due to the high volume of visits, significant variability in patient arrival patterns, and the urgency of the care required. Draeger (1992) studies nurse workload in an emergency room and its effect on the average number of patients, average time in system, average number of patients waiting, and average patient waiting time. Comparing the current schedule's performance to those of two alternative staffing schedules, the author found an alternative that could reduce both the average patient time in system (by 23%) and the average patient waiting time (by 57%), without any increase in costs. Similarly, Evans et al. (1996) reduce a patient's length of stay by finding the optimal number of nurses and technicians that should be on duty during four shifts in an emergency room. Kumar and Kapur (1989) examine ten nurse scheduling policy alternatives, selecting and implementing the policy yielding the highest nurse utilization rate.

Lambo (1993) applies a recursive linear programming and discrete-event simulation methodology to examine staffing problems in a health care center in Nigeria. In the study, the clinic was observed to be at 50% capacity due to the misallocation of (rather than the inadequacy of) personnel. After making changes to the staffing patterns and other policy changes, capacity increased by 60% and patient waiting times were reduced by 45 minutes. In a similar study, Chan et al. (2002) uses integer programming and discrete-event simulation to study a medical records department to determine the optimal staff schedule and understand the workflow of the transcription function.

All of these discrete-event simulation studies suggest that when patient flow patterns cannot be controlled, staffing strategies can be employed to smooth some of the unavoidable variability in the systems. This can result in improved patient throughput, while keeping staff utilization rates and total staffing costs at acceptable levels. It may also act as an important public

relations and marketing tool. Health care is unique in that quality is not always readily identifiable by its customers. A patient whose condition improves may have received quality care; however, if services were delivered inefficiently, the patient's perception of quality may be greatly diminished. Efficient patient flow, then, often acts as a surrogate for quality of care in the patient's mind. Given a choice, patients will tend to a health care provider they perceive to offer higher quality services. Moreover, facilities that minimize the obstacles to the provision of care for health care providers (e.g., physicians, nurses) are better able to attract and retain the best and brightest. In short, patient flow is not just important to the bottom line, but it can serve as a major competitive advantage.

2.2 Health Care Asset Allocation

Hospital and clinic administrators have approached cost containment within their operations by working to minimize expenditures for health care provisions while simultaneously providing quality health care services. Such situations pervade the health care community as indicated by the large number of papers and studies that analyze the allocation of scarce health care assets. Discrete-event simulation modeling is an attractive method to help make such allocations since it can be used to estimate the operational characteristics of a health care system operation and to observe the impact of changes in planning or policies prior to the implementation of such changes, and thereby mitigate financial risks. The allocation of health care assets can be broken down into three general areas where assets most directly impact health care delivery: bed sizing and planning, room sizing and planning, staff sizing and planning.

2.2.1 Bed Sizing and Planning

The demand for hospital beds can be classified as either routine (e.g., scheduled) or emergency (e.g., unscheduled) admissions. Both of these admission types impact how many beds are needed to meet demand, while maintaining reasonable bed utilization rates. In the literature, most bed planning discrete-event simulation models attempt to overcome bed shortages or policies that lead to patient misplacement, bumping, or rejection. Hospitals are typically faced with the tradeoff between having available beds to service patient demand versus keeping bed occupancy (utilization) rates high.

Butler et al. (1992a) use discrete-event simulation to study patient misplacements, where patients are scheduled and assigned to an alternative unit within a hospital due to a shortage of beds in the preferred hospital area.

They examine the sensitivity of patient misplacement with respect to a variety of modifications in their bed allocation policy, including patient transfers, bed scheduling, and assignments, and found that reducing a patient's length of stay and reallocating rooms among the different services within a hospital could substantially decrease patient misplacement. Furthermore, the smoothing of routine patient arrivals only marginally reduced patient misplacement. In another study designed to reduce patient misplacement, Butler et al. (1992b) use a two-phase approach involving a quadratic integer programming model and a discrete-event simulation model to evaluate bed configurations and to determine optimal bed allocations across a number of hospital service areas. Vasilakis and El-Darzi (2001) use discrete-event simulation to identify the possible cause for a hospital bed crisis that occurs each winter in United Kingdom National Health Services hospitals. Using simulation, they demonstrate a "breakdown in the discharge of dependent patients from the medium stay (or rehabilitative) stream" because during the Christmas and New Year holiday season surgeons are not performing routine operations. However, once surgeons return to work after the holidays, the resulting surge in the number of surgeries scheduled results in an insufficient number of beds for incoming medical emergencies. The study suggests that the UK winter bed crisis is likely due to staff scheduling, the holidays, and ineffective management of non-acute (longer stay) patients. Note that US hospitals typically experience such "winter census" crises, as well.

Lowery (1992, 1993) and Lowery and Martin (1992) consider the use of discrete-event simulation in a hospital's critical care areas (e.g., operating rooms, recovery units, intensive care units, and intermediate care units) to determine critical care bed requirements. Their literature review reveals that most models do not fully consider the interrelationships between different hospital units and few models have been validated using actual hospital performance data. Focusing on these deficiencies, they demonstrate improvements in their methodologies over previous models. Dumas (1984, 1985) also focuses on the interrelationships between several units within a hospital by comparing two bed planning rules (vacancy basing and home basing) for locating a bed within different hospital units when a patient cannot be allocated a bed at the preferred unit. Vacancy basing rules employ a ranked list of alternative misplacement possibilities, while home basing prohibits off-service misplacements, and hence, is more restrictive with respect to patient placement. They show that home basing policies result in better overall performance but lessen patient days and thereby reduce hospital revenues. Note that in the mid-1980s (the time of Dumas' publications) most hospitals were still paid by third party providers based on

the patient's overall length of stay, so reducing patient days was seen as a potentially negative outcome. In contrast, modern reimbursement systems tend to favor case rates that encourage shorter lengths of stay, ultimately resulting in an incentive for hospitals to reduce patient days.

Cohen et al. (1980) present a bed planning model of a progressive patient care hospital, where patients are moved between units within a hospital as their condition changes. In this form of demand-matching, hospitals attempt to apply resources commensurate with patients' condition during their stay by "stepping the patient down" as their conditions improve. The authors demonstrate that the probability of inappropriate patient placement is a function of the capacities of all the units, as well as the policies for handling priority patients and bumped patients.

By considering individual units within a hospital, Zilm et al. (1983) use a discrete-event simulation model to analyze a surgical intensive care unit for various bed levels and future demand. They observe that most of the unit's volume consists of weekday cases (routine admissions), and hence, attempts to maintain a high overall average occupancy level would not be possible without straining the entire system. Similarly, Cahill and Render (1999) study proposed changes to the intensive care unit (ICU) at the Cincinnati Veterans Administration Medical Center. Using discrete-event simulation, they show that creating a respiratory care unit and increasing bed levels in other units closely associated with the intensive care unit would resolve the ICU access problems. However, an increase in ICU bed availability increased bed utilization in other units, which in turn increased the overall length of stay. Therefore, modeling in advance helped the hospital identify policy changes to lessen the impact on length of stay. Masterson et al. (2004) discuss the optimization of the military health system for all military health facilities. They present a case study based on a simulation analysis of the intensive care unit at the US Air Force's Wilford Hall Medical Center, to determine the appropriate ICU size, bed mix, and staffing level.

Romanin-Jacur and Facchin (1987) use discrete-event simulation to study the facility dimensioning problem and the sizing of the assistance team in a pediatric semi-intensive care unit. They compare several different priority-based models by using peak admission conditions to find the optimal number of beds and the best choice of the nurse's care assignment. Other bed sizing discrete-event simulation models can be found in Hancock et al. (1978), Wright (1987), Harris (1985), Wiinamaki and Dronzek (2003), and Akkerman and Knip (2004). Harris (1985) compares the difference in the number of surgical suites needed in a surgical center for three physicians under two operating timetable scenarios. Under the first (and current) scenario, each physician scheduled his/her patients independently of the other two physicians, while in the second scenario, the physicians pooled

their resources to schedule their patients and consequently reduced the number of surgical suites required by over 20%. Wiinamaki and Dronzek (2003) show how simulation was used in determining the bed requirements for the new emergency care center at the Sarasota Memorial Hospital in Sarasota, Florida. Akkerman and Knip (2004) show that the number of beds could be reduced in a cardiac surgery center if recovering patients are transferred once they no longer require the center's specialized care services.

Gabaeff and Lennon (1991) use an extensive time-motion study to collect data on the mix of patient types, patient characteristics (such as x-ray requirements), and staffing mix for emergency admissions in an emergency department feasibility study at Stanford University Hospital. Using discrete-event simulation models, they highlight deficiencies in several key areas, including maximum bed utilization exceeding current bed availability (which would cause displacement of minor care patients). Vassilacopoulos (1985) develops a discrete-event simulation model to determine the number of beds with the following constraints: high occupancy rates, immediate (emergency admission) patients, and low length of waiting lists. He shows that by using a waiting list and smoothing the patient demand, it is possible to achieve high occupancy rates. Emergency department bed planning discrete-event simulation models are also discussed by Altinel and Ulas (1996) at the Istanbul University School of Medicine, Freedman (1994) at St. Joseph Hospital and Washington Adventist Hospital in Maryland, USA, Lennon (1992) at the Stanford University Hospital, and Williams (1983) at the University of Pennsylvania Hospital. All these studies suggest that discrete-event simulation modeling and analysis provides a valuable "what if" tool for hospital planners when deciding how many beds are needed to meet demand and maintain profitability. It also assists decision-makers in judiciously allocating precious financial resources. The ever-increasing costs of medical equipment (e.g., CT scanners) mean that health care administrators must preserve capital for technology that historically could have been allocated to brick-and-mortar expansions. Simulation modeling can play an important role in this effort. Moreover, simulation models allow hospital administrators to experiment with different bed allocation rules to help optimally utilize hospital facilities and improve bed occupancy rates.

2.2.2 Room Sizing and Planning

The ongoing movement towards freestanding surgicenters, as well as the shift to deliver health care services away from inpatients facilities and towards outpatient facilities, has put increased pressure upon hospital management to expand their outpatient services and/or to build new facilities

to handle these additional patient demands. Discrete-event simulation has become an important tool for the planning of future expansion, integration, and/or construction of new outpatient facilities and health service departments, by significantly enhancing the hospital administration decision-maker's ability to find the most cost-effective and efficient solutions to such problems.

The number and use of operating rooms is often an important resource in maintaining hospital profitability and patient services. Currie et al. (1984) study operating room utilization, vertical transportation needs, radiology staffing, and emergency medical system operations at the West Virginia University Hospital. They use discrete-event simulation to estimate the number of operating rooms and recovery beds needed to handle a 20% increase in future demand. Kwak et al. (1975) use discrete-event simulation to determine the capacity of a recovery room needed to support an operating room expansion. Similarly, Kuzdrall et al. (1981) use a discrete-event simulation model of an operating and recovery room facility to determine and assess the facility utilization levels and facility needs under different scheduling policies. Olson and Dux (1994) apply discrete-event simulation modeling to study and evaluate the decision to expand the Waukesha Memorial surgicenter from seven to eight operating rooms. Their study reveals that an eighth operating room would only serve to meet the hospital's needs for no more than two years, at a cost of $500,000 (USD). However, an analysis of the cross-departmental and administrative needs reveal that an ambulatory surgery center that separates the inpatients and outpatient procedures would better serve the hospital's future health care delivery needs. Similarly, Amladi (1984) uses discrete-event simulation to help size and plan a new outpatient surgical facility, by considering patient wait time (quality) and facility size (resource). Lowery and Davis (1999) developed a discrete-event simulation to assess the impact of a proposed renovation to the surgical suite of Brigham and Women's Hospital in Boston, Massachusetts, USA. Hospital administrators wanted to ensure that the renovations would be sufficient to handle a projected increase in the number of inpatient surgeries. The simulation showed the projected increases could be met with 30 or less operating rooms (32 operating rooms were planned in the renovation) provided scheduled block times were extended to include the addition of a Saturday block.

Ferrin et al. (2004) apply discrete-event simulation to help St. Vincent's Hospital in Birmingham, Alabama, USA, a not-for-profit hospital, determine the value of implementing an incentive program for their operating room environment. The simulation showed that improving the room turnaround process by 20% would result in a 4% improvement in the operating rooms case volume and a 5% increase in utilization of same day surgical rooms.

This increase in volume provided enough increase in revenue to justify an incentive to improve the operating room turnaround process. In addition to evaluating the value of incentives, St Vincent's administration used the simulation to determine the required number of operating rooms, number of beds in the Post Anesthesia Care Unit (PACU), and changes in physician scheduling blocks.

Meier et al. (1985) use discrete-event simulation to compare and evaluate eleven scenarios in varying the number of exam rooms and demand shifts of both a hospital ambulatory center and a freestanding surgicenter. They found that existing room capacity is adequate to handle demands over the next five years. Iskander and Carter (1991) use discrete-event simulation to show that current facilities were sufficient for future growth in a study of a same day (outpatient) health care unit in an ambulatory care center. However, they suggest a threefold increase in the size of the waiting room. Using discrete-event simulation, Ramis et al. (2001) evaluate a proposed future center for ambulatory surgery by evaluating several process alternatives. The results determined the bed resources and scheduling rule required to maximize daily surgical throughput. Similarly, Stahl et al. (2003) seek to optimize the management and financial performance of ambulatory care clinics used for teaching medical students. Here they use discrete-event simulation to determine that a teaching ambulatory care clinic runs optimally (where optimality is defined as the policy that minimizes patient flow time and wait time while maximizing revenue) when the trainee-to-preceptor ratio is between 3 and 7 to 1.

Kletke and Dooley (1984) use discrete-event simulation to examine the effects on service level and utilization rates in a maternity unit to determine if the current number of labor rooms, delivery rooms, post-partum rooms, nursery, and nurses are able to meet future demands. Their study recommends increasing the number of labor rooms and the number of post-partum rooms, while maintaining four full-time nurses. Levy et al. (1989) use discrete-event simulation to analyze the operational characteristics of an outpatient service center at Anderson Memorial Hospital to determine whether to merge this service with an off-site outpatient diagnostic center. They collected data on the utilization of the servers, the total number of patients in the center, the maximum and average times spent in the center, the maximum and average times spent in each service queue, and the total number of patients in each queue. This information was used to specify staffing and facility sizing requirements. In another facility integration plan, Mahachek and Knabe (1984) use discrete-event simulation to evaluate a proposal to cut costs by combining an obstetrics clinic and a gynecology clinic into a single facility. The analysis found that this proposal would not

be successful due to the shortage of exam rooms. All these studies illustrate the value provided by discrete-event simulation modeling and analysis to determine how to set the size of key hospital facilities (such as operating rooms). As the health care industry continues to move more towards outpatient delivery systems, and away from traditional inpatient health care facilities, discrete-event simulation will continue to assist health care decision-makers in leveraging their resources in undertaking such transitions.

2.2.3 Staff Sizing and Planning

The medical community requires highly skilled staff to delivery quality health care services, making staff sizing and planning an important factor in designing health care delivery systems (such as those found in hospitals). Moreover, the tradeoff between insufficient clinical staff to meet demand (hence unacceptable patient waiting times) and underutilization of clinical staff can have an enormous impact on the economic viability and sustainability of a medical facility. Discrete-event simulation has played an important role in addressing the issues inherent in this trade-off.

Several discrete-event simulation studies have been conducted to determine the staff size or the number of physicians for emergency departments (e.g. Carter et al. 1992). Badri and Hollingsworth (1993) analyze the impact of different operational scenarios on scheduling, limited staffing, and changing the patient demand patterns in an emergency room of the Rashid Hospital in the United Arab Emirates. These scenarios included using a patient priority rule based on severity of ailment, not serving a category of patient that does not belong in the emergency room, eliminating one or more doctors on each shift, and a hybrid scenario that combines the last two scenarios. The results from this hybrid scenario were accepted and implemented. Klafehn and Owens (1987) and Klafehn et al. (1987) address the problem of determining the relationship between patient flow and the number of staff available in an emergency department. They conclude that moving one nurse from the regular emergency area to a triage position significantly reduces patient waiting lines and waiting times. Furthermore, they found that the addition of a second orthopedic team in the emergency department increases patient throughput, though utilization levels were lower and the average length of stay remains virtually the same (since the number of patients flowing through the orthopedic area was relatively small). Liyanage and Gale (1995) formulate an M/M/n queuing model of the Campbelltown Hospital emergency facility to estimate and develop patient arrival time distributions, patient waiting times, and patient service times. These parameters were then used in a discrete-event simulation

model to estimate the expected patient waiting times, the expected physician idle times, and the optimal number of doctors. Baesler et al. (2003) use a discrete-event simulation model to predict a patient's time spent in the emergency room of a private hospital in Chile. These results were then used in a design of experiments to minimize the number of resources (four full-time physicians and one part-time physician) required to meet patient demand. Similarly, Centeno et al. (2003) combine discrete-event simulation with integer programming to develop an optimal schedule for emergency room staff. The study showed a 28% improvement over the current method of staffing which offers a potential significant savings in hospital labor costs. Lopez-Valcarcel and Perez (1994) use discrete-event simulation to evaluate the staffing levels, the arrival rates, and the service times of diagnostic equipment (alterable by purchasing better equipment) in an emergency department. They recommend that the arrival rate should not exceed twelve patients per hour. Moreover, they recommend that investments in human resources would be more effective than investments in newer (better) equipment. In contrast, Bodtker et al. (1992) and Godolphin et al. (1992) determine that a reduction in staff by at least one staff member could be achieved if better equipment were purchased.

O'Kane (1981), Klafehn (1987), and Coffin et al. (1993) use discrete-event simulation to analyze staff allocations to improve patient flow in a radiology department. Klafehn and Connolly (1993) model an outpatient hematology laboratory and compare several configurations. They observed that if the staff is cross-trained (and hence, can be more fully utilized), then patient waiting times can be reduced. Vemuri (1984) and Ishimoto et al. (1990) use discrete-event simulation to identify the optimal medical staff size and mix that reduces patient waiting times in a hospital pharmacy. Weng and Houshmand (1999) simulate a general hospital outpatient clinic to find the optimal staff size that maximizes patient throughput and minimizes patient flow time.

Jackson Memorial Hospital (JMH) in Dade County, Florida, USA uses discrete-event simulation to model hospital operations. Centeno et al. (2001) present a simulation study of the labor and delivery rooms at JMH. This study used historical data for all simulation inputs and identified ways to improve physician scheduling and better staffing levels. A simulation study of the radiology department at JMH is discussed in Centeno et al. (2000). Six different scenarios, that vary staff and physical resources, are studied to determine the impact on patient flow and utilization of the department staff and operating rooms. This study determined the most cost-effective staff level for each procedure and identified additional revisions to improve process and service efficiencies.

Hashimoto and Bell (1996) conduct a time-motion study to collect data for a discrete-event simulation model of an outpatient (general practice) clinic. They show that increasing the number of physicians, and consequently the number of patients, without increasing the support staff, would significantly increase patient length of stay. By limiting the number of physicians to four and increasing the number of dischargers to two, they were able decrease the patient's average total time in the system by almost 25%. Wilt and Goddin (1989) use discrete-event simulation to evaluate patient waiting times to determine appropriate staffing levels in an outpatient clinic. McHugh (1989) uses discrete-event simulation to examine hospital nurse-staffing levels and their impact on cost and utilization. This analysis shows that 55% of the maximum workload produces the best results based on these measures. Swisher et al. (2001) discuss a discrete-event simulation model of the Queston Physician Practice Network where individual family outpatient clinics are modeled and integrated into a network of clinics that uses a central appointment scheduling center. Performance measures such as patient throughput, patient waiting time, staff utilization, and clinic overtime are analyzed for various numbers of exam rooms and staff mixes. In certain cases, adding support personnel had negligible effects on the performance measures. Swisher and Jacobson (2002) use an object-oriented visual discrete-event simulation to evaluate different staffing options and facility sizes for a two physician family practice health care clinic. They describe a clinic effectiveness measure that is used to evaluate the overall effectiveness of a given clinic configuration. This clinic effectiveness measure integrates clinic profits, patient satisfaction, and medical staff satisfaction into a single performance measure.

Rossetti et al. (1998) use discrete-event simulation to study clinical laboratory and pharmacy delivery processes in a mid-size hospital environment. The study specifically assesses the costs and performance benefit of procuring a fleet of mobile robots to perform delivery functions. The study found that a fleet of six mobile robots improved the turn-around time by 33% and reduced costs by 56% compared to the current system of three human couriers. Similarly, Wong et al. (2003) use simulation "to quantify the advantages of an electronic medication ordering, dispensing, and administration process" at an academic acute care center. The automated system had an average turnaround time of 123 minutes versus the current manual system turnaround time of 256 minutes. Dean et al. (1999) also study a hospital pharmacy distribution system, where they use simulation to help determine when a pharmacist should visit each nursing unit to minimize the mean time delay between the time when a prescription is filled and its arrival to the ward.

Stafford (1976) and Aggarwal and Stafford (1976) develop a multi-facility discrete-event simulation model of a university health center that incorporates fourteen separate stations (e.g., receptionist area, injections, dentist, gynecology, physical therapy, radiology, and pharmacy). Using student population figures and seven performance measures, they were able to estimate the level of demand for services in the clinic. They also show that patient inter-arrival times are distributed negative exponential with the mean changing according to the time of day, and patient service times are distributed Erlang-K. Using these data, they investigate the effects of adding another pharmacist to the pharmacy. A multi-factor experimental design was developed to examine the relationships between the controllable system variables and the system performance variables. They show that different calling population sizes and different levels of staffing can impact the performance measures at each station. Additionally, the aggregation of two or more similar facilities can cause an increase in the average number of patients waiting at each of the remaining facilities and the average patient waiting times, though these increases were offset by a significant decrease in the staff idle times and staff costs. These studies suggest that staffing levels and staff distributions have a significant impact on patient throughput and waiting times. As with facility sizing and planning, discrete-event simulation can be an effective tool to study various staffing strategies for a wide variety of health care facilities and systems. As the national shortage of skilled clinicians (particularly nurses) deepens, such studies will become increasingly important to health care organizations as they attempt to optimally deploy scarce human resources.

3. RECENT INNOVATIONS AND FUTURE DIRECTIONS

There is a growing amount of literature on using discrete-event simulation to study the design and operation of health care delivery systems. Publications based on such studies have steadily increased from eight in 1973-1977 to twenty-eight in 1993-1997 to over fifty in 1998-2004. This positive trend can be attributed to the increasing demand for cost-cutting in health care coupled with an increase in the ease-of-use and power of discrete-event simulation software packages (especially over the past decade). A growing number of these studies attempt to apply optimization techniques to analyze discrete-event simulation models. Despite the increase in health care simulation studies and the integration of discrete-event simulation and optimization techniques, few studies focus on complex

integrated systems. This may be a result of the associated complexity issues and resource requirements required for such studies. Moreover, no matter how complex modeled systems are or what techniques are applied, it will continue to be a challenge to implement the results of such studies. However, recent advances in discrete-event simulation software may help to overcome some of these obstacles.

Most discrete-event simulation models focus on individual units within multi-facility clinics or hospitals. Using a macroscopic analysis of multi-facility systems, discrete-event simulation can be used to estimate patient demand (directly related to arrival rates), utilization of staff, and overall costs. The estimation of these performance measures may not be possible in a microscopic, single level model, due to the duplication of and overlapping of facilities and services. Discrete-event simulation models that capture the interaction of major service departments and support services in a hospital, and the information that can be gained from analyzing the system as a whole, can be invaluable to hospital planners and administrators.

To remain competitive in today's market, the health care industry is being forced to integrate hospitals and clinics, especially the ever-growing number of ambulatory care facilities, into health maintenance organizations (HMO), multi-hospital, or multi-clinic organizations. This presents a challenging application for discrete-event simulation: to operate these networks of clinics or departments efficiently and cost effectively. Studies in multi-facility simulation models have been conducted by Rising et al. (1973), Aggarwal and Stafford (1976), Hancock and Walters (1984), Swisher et al. (1997, 2001), and Lowery and Martin (1992).

A benefit from simulating integrated systems is the more realistic representation of the system under study, hence greater confidence in the results. Though this may not be significant when analyzing a small system, the consequences of invalid results or the lack of a thorough study may potentially be a costly decision for large multi-million dollar organizations. With this potential benefit, the question that has to be asked is: Why is there a lack of literature in this area? The answer may lie in one or both of two issues: (1) the level of complexity and resulting data requirements of the simulation model and/or (2) the resource requirements, including time and cost.

A widely recognized guideline in discrete-event simulation modeling is to keep the model as simple as possible while capturing the necessary measures of interest. This is reiterated by Dearie et al. (1976) who stress the importance of capturing only relevant performance variables when creating a simple, though not necessarily the most complete model. They suggest that it is best to depict the various subsystems at the lowest level of complexity such that the model is accurate while providing information that is easily

interpreted. Moreover, Lowery (1996) suggests using simple analytical models if they can provide the necessary level of detail. However, when analyzing integrated systems, the level of detail that is required far exceeds the complexity and demands of analytical techniques. Therefore, care must be taken when determining the required level of detail (since more detail typically means that more data must be collected). The soft system methodology (SSM), an approach that aids in determining the level of detail, identifying system boundaries, and ascertaining system activities, is suggested by Lehaney and Paul (1994, 1996) and Lehaney and Hlupic (1995). Through increased participation of the users/customers, SSM encourages acceptability of the model, its results, and eventually the model's implementation.

Resource requirements, such as the length of time, the cost, and the skills necessary to complete the project must be fully considered before commencing such a large-scale project. Today's health care delivery environment is rapidly changing and if the process of developing and searching for a solution requires a large investment in time and resources, the system may be outdated before the results from the simulation study can be implemented. Consequently, an adequate amount of resources must be dedicated to the project to ensure completion of the study in a reasonable length of time. For example, the cost of collecting the required data (in terms of time and money), the cost of purchasing a discrete-event simulation software package that would ease the development of complex models, and the cost of skilled consultants or in-house engineers may all be prohibitive.

Given that discrete-event simulation is not an optimization tool, it can only provide estimates of performance measures for various system alternatives. Moreover, discrete-event simulation models typically have several output performance measures upon which to optimize, hence creating a multi-criteria objective function environment. There are several advantages and disadvantages of using either discrete-event simulation methodologies or optimization techniques to model complex systems. Karnon (2003), Davies and Davies (1994) and Stafford (1978) compare discrete-event simulation modeling to several techniques, such as Markov chain analysis, semi-Markov chain analysis, input-output analysis, and queuing analysis of an outpatient clinic. They find that discrete-event simulation is particularly well suited for modeling health care clinics due to the complexity of such systems, whereas many optimization techniques, such as linear programming, have a limited capacity for characterizing the complexities of medical systems. An optimization technique may require too many unrealistic assumptions about the process, hence rendering the solution invalid and unrealistic. For example, optimization models cannot

be used to study the details of the day to day operations of a medical clinic, such as appointment scheduling, service routing, and service priorities, which can be easily captured by a discrete-event simulation model. On the other hand, many optimization models require only one experimental run to produce optimal or near optimal solutions, though the complexity of the model may result in an intractable solution; whereas, discrete-event simulation models require a large amount of effort in time, cost, and data collection. For all of these reasons, operations researchers have attempted to combine simulation with deterministic operations research techniques, such as linear programming, to simultaneously exploit the advantages of using both techniques.

Several studies have reported success in combining these techniques to find the best staffing allocations and facility sizes. A common technique when applying an optimization methodology to discrete-event simulation models of health care clinics is a recursive method employed by Carlson et al. (1979), Kropp et al. (1978), and Kropp and Hershey (1979). First, an optimization technique is used to analyze and reduce the number of alternatives of the system at an aggregate level (i.e., the total system level). These results are then used in a more complex and detailed discrete-event simulation model of the same system, which is then used to identify additional information and validate the results. Finally, these additional constraints are passed back into the optimization model and this process is iteratively repeated. Similarly, Butler et al. (1992b,c) employ a two phase approach by first using quadratic integer programming for facility layout and capacity allocation questions, and then a discrete-event simulation model to capture the complexities of alternative scheduling and bed assignment problems. Baesler and Sepúlveda (2001) extend the study of Sepúlveda et al. (1999) by using a simulation model of a new cancer treatment facility as a case study for solving a multi-objective (minimize patient waiting time, maximize chair utilization, minimize closing time, maximize nurse utilization) simulation optimization problem.

All of these studies use a variety of optimization techniques to arrive at parameters for the discrete-event simulation models. In general, recursive simulation optimization techniques can be very difficult, and therefore, costly to implement in the health care sector. However, a growing number of simulation software packages have appeared that provide an optimization add-on (Carson and Maria 1997). Instead of an exhaustive, time-consuming, and indiscriminate search for an optimal alternative, discrete-event simulation software companies are now starting to provide special search algorithms to guide a simulation model to an optimal or near-optimal solution. Examples of these include an add-on to MicroSaint 2.0 called OptQuest, that uses a scatter search technique (based on tabu search) to find

the best value for one or multiple objective functions (Glover et al. 1996). Other optimization simulation software includes ProModel's SimRunner Optimization (Benson 1997) and AutoStat for AutoMod (Carson 1996).

Since their introduction, discrete-event simulation software packages have gone through a series of technological leaps and advances. First, the introduction of visually-oriented graphical outputs has greatly aided in the verification and validation of models and results (Gipps 1996, Sargent 1992), though this does not necessarily guarantee model correctness (Paul 1989). Moreover, discrete-event simulation model animation is primarily used to present movie-like images of the actual operation of the model and system which, in essence, helps to sell insights into the system under study. Second, the wide use of the object-oriented paradigm (OOP) in discrete-event simulation software design enables analysts to model a system without writing a single line of code (Banks 1997). Numerous companies are developing general-purpose software packages incorporating the latest technologies (Banks 1996), with packages like MedModel (Harrell and Lange 2001, Harrell and Price 2000, Price and Harrell 1999, Heflin and Harrell 1998, Carroll 1996, Keller 1994) and ARENA with a health care template (Drevna and Kasales 1984) specifically aimed to serve the health care industry.

Jones and Hirst (1986) present one of the early articles on using visual simulation, using the discrete-event simulation software package See-Why. The visualization of different policies in the visual simulation of a surgical unit and surrounding resources plays an integral part in assisting managers in identifying the best solutions. Paul and Kuljis (1995) use CLIMSIM, a generic discrete-event simulation package, to illustrate how clinic appointments and operating policies can influence patient waiting time. Evans et al. (1996) use ARENA to model an emergency department using thirteen patient categories. They reduce patients' length of stay using alternative scheduling rules for the number of nurses, technicians, and physicians on duty during each particular hour of the simulation run. In addition to these studies, several other visual simulation modeling project of interest have been conducted (including McGuire, 1994 and Ritondo and Freedman, 1993).

The number of health care organizations and government agencies using advanced discrete-event simulation software packages has grown, with much of their work and the results of their efforts not available in the open literature. Considering the number of easy to use discrete-event simulation software packages available today, it seems unusual to find that such a small number of visually-oriented simulation models of health care clinics have been published. This may be attributed to the shifting face of simulation

modelers. As discrete-event simulation models have become easier to build with new software packages, the type of users have also changed. Since it is no longer necessary to have an advanced technical degree to use discrete-event simulation software packages (due largely to the drag-and-drop operation of such packages), numerous non-technical (and typically non-publishing) users have emerged. However, this development does not diminish the importance of contributions from operations research professionals to the health care field, since such individuals will continue to be needed to provide technical expertise when conducting or managing critical or large-scale discrete-event simulation projects.

Discrete-event simulation modeling of health care clinics has been extensively used to assist decision-makers to identify areas of service where efficiencies can be improved. For discrete-event simulation to reach its full potential as the key tool for analyzing health care clinics, the results from such simulation studies must be implemented. Unfortunately, in a survey of two hundred papers reporting the results of discrete-event simulation studies in health care, Wilson (1981) found that only sixteen projects reported successful implementations. A number of recommendations were given to increase the opportunities for and likelihood of implementation success. These recommendations include: the system being studied is actually in need of a decision, the project must be completed before a deadline, data must be available, and the organizer or the decision-maker must participate in the project.

Lowery (1998, 1996, 1994) addresses some additional implementation barriers, as well as solutions to help overcome the resistance to implementation. Some of the suggestions include animating the simulation model execution to more easily communicate the problem and the solution to the decision-maker, making sure management stays involved throughout the project, and avoiding too many assumptions or making the model too complex. She also suggests that management engineers must simplify the simulation process and improve their sales skills. Marsh (1979) lists three key elements necessary for the successful implementation of simulation results: total commitment and support from the users, credibility of the model, and the analyst must work with the real operations under study rather than any esoteric studies.

Despite the lack of implementation observed in the literature, other benefits can still be gained from conducting a discrete-event simulation study. The procedure and methodology of applying discrete-event simulation requires decision-makers and managers to work closely with the simulation analyst to provide details of the system, often for the first time. As a result, the manager is likely to gain a new perspective on the relationships between the available resources and the quality of health care

services offered by the system. Rakich et al. (1991) study the effects of discrete-event simulation in management development. They conclude that conducting a simulation study not only develops a manager's decision-making skills, but also forces them to recognize the implications of system changes. Moreover, as also noted Wilson (1981), in the cases where managers developed their own discrete-event simulation models, implementation occurred much more frequently. Finally, Lowery (1996) notes that there are benefits, such as identifying unexpected problems unrelated to the original problem, which arise even if implementation fails.

4. SUMMARY AND CONCLUSIONS

In conclusion, this chapter surveys the literature (focusing primarily on the past thirty years) on the application of discrete-event simulation modeling and analysis to understand the operations of health care facilities. A significant amount of research has been conducted in the area of patient flow and asset allocation. The multiple performance measures associated with health care systems makes discrete-event simulation particularly well-suited to tackle problems in these domains. A large number of discrete-event simulation studies reported in the literature have the common theme that they attempt to understand the relationship that may exist between various inputs into a health care delivery system (e.g., patient scheduling and admission rules, patient routing and flow schemes, facility and staff resources) and various output performance measures from the system (e.g., patient throughput, patient waiting times, physician utilization, staff and facility utilization). The breadth and scope of units within hospitals and clinics makes it impossible to undertake a single comprehensive study that simultaneously addresses all of these issues.

The aforementioned observations, together with the dearth of literature in the area of complex integrated multi-facility systems, suggest the need to develop a comprehensive simulation modeling framework for determining clinical performance measures and interdepartmental resource relationships. Furthermore, this survey identified a number of continuing trends in discrete-event simulation software such as: the development of optimization add-ons, increased visualization, and the shift to an object-oriented paradigm. These powerful features will have the greatest impact when educating decision-makers on what changes need to be made and weakening the resistance to implementation. The outlook for discrete-event simulation in health care looks promising. The further development of more powerful high speed processing, distributed simulations (Baezner et al. 1990), and

object-oriented simulation, will facilitate the creation of complex, but tractable, models of large integrated systems. Greater decision-maker buy-in will lead to model results being implemented more easily and frequently, providing greater opportunities for success. Twenty-first century health care decision-makers are faced with a complex and challenging environment. Costs are rising, human and fiscal resources are becoming scarcer, consumer expectations are rising, and technology is becoming more complex. It is crucial that health care managers make informed decisions on health care policies and the application of resources. Discrete-event simulation offers perhaps the most powerful and intuitive tool for the analysis and improvement of complex health care systems.

5. REFERENCES

S.C. Aggarwal and E.F. Stafford, 1976, A simulation study to identify important design parameters of a typical outpatient health system and to analyze measures of its performance, *Proceedings of the 1976 Summer Computer Simulation Conference*, Simulation Council, Washington, DC, USA, 12-14 July, 544-553.

R. Akkerman and M. Knip, 2004, Reallocation of beds to reduce waiting time for cardiac surgery, *Health Care Management Science,* **7**:119-126.

A.J. Alessandra, T.E. Grazman, R. Parameswaran, and U. Yavas, 1978, Using simulation in hospital planning, *Simulation*, **30**(2): 62-67.

A. Alexopoulos, D. Goldsman, J. Fontanesi, M. Sawyer, M. De Guire, D. Kopald, and K. Holcomb, 2001, A discrete-event simulation application for clinics serving the poor, *Proceedings of the 2001 Winter Simulation Conference* (B.A. Peters, J.S. Smith, D.J. Medeiros, M.W. Rohrer, Editors), Institute of Electrical and Electronics Engineers, Arlington, Virginia, USA, 9-12 December, 1386-1391.

I.K. Altinel and E. Ulas, 1996, Simulation modeling for emergency bed requirement planning, *Annals of Operations Research*, **67**:183-210.

P. Amladi, 1984, Outpatient health care facility planning and sizing via computer simulation, *Proceedings of the 1984 Winter Simulation Conference* (S. Sheppard, U.W. Pooch, C.D. Pegden, Editors), Institute of Electrical and Electronics Engineers, Dallas, Texas, USA, 28-30 November, 705-711.

M. Badri and J. Hollingsworth, 1993, A simulation model for scheduling in the emergency room, *International Journal of Operations and Production Management*, **13**(3):13-24.

F.F. Baesler, H.E. Jahnsen, and M. DaCosta, 2003, The use of simulation and design of experiments for estimating maximum capacity in an emergency room, *Proceedings of the 2003 Winter Simulation Conference* (S. Chick, P.J. Sánchez, D. Ferrin, D.J. Morrice, Editors), Institute of Electrical and Electronics Engineers, New Orleans, Louisiana, USA, 7-10 December, 1903-1906.

F.F. Baesler and J.A. Sepúlveda, 2001, Multi-objective simulation optimization for a cancer treatment center, *Proceedings of the 2001 Winter Simulation Conference* (B.A. Peters, J.S. Smith, D.J. Medeiros, M.W. Rohrer, Editors), Institute of Electrical and Electronics Engineers, Arlington, Virginia, USA, 9-12 December, 1405-1411.

D. Baezner, G. Lomow, and B.W. Unger, 1990, Sim++™: The transition to distributed simulation, *Proceedings of the 1990 SCS Western Multiconference on Simulation:*

Distributed Simulation (D Nicol, Editor), Society for Computer Simulation, San Diego, California, USA, 17-19, January, 211-218.

N.T. Bailey, 1952, A study of queues and appointment systems in hospital outpatient departments, with special reference to waiting times, *Journal of the Royal Statistical Society*, **A14**:185-199.

L.P. Baldwin, T. Eldabi, and R.J. Paul, 2004, Simulation in healthcare management: a soft approach (MAPIU), *Simulation Modelling Practice and Theory*, **12**:541-557.

J. Banks, 1996, Software for Simulation, *Proceedings of the 1996 Winter Simulation Conference* (J.M. Charnes, D.M. Morrice, D.T. Brunner, J.J. Swain, Editors), Institute of Electrical and Electronics Engineers, Coronado, California, USA, 8-11 December, 31-38.

J. Banks, 1997, The future of simulation software: A panel discussion, *Proceedings of the 1997 Winter Simulation Conference* (S. Andradottir, K.J. Healy, D.E. Withers, B.L. Nelson, Editors), Institute of Electrical and Electronics Engineers, Atlanta, Georgia, USA, 7-10 December, 166-173.

J. Banks and J.S. Carson, 1987, Applying the simulation process, *Proceedings of the 1987 Winter Simulation Conference* (A. Thesen, H. Grant, W.D. Kelton, Editors), Institute of Electrical and Electronics Engineers, Atlanta, Georgia, USA, 14-16 December, 68-71.

D. Benson, 1997, Simulation modeling and optimization using ProModel, *Proceedings of the 1997 Winter Simulation Conference* (S. Andradottir, K.J. Healy, D.E. Withers, B.L. Nelson, Editors), Institute of Electrical and Electronics Engineers, Atlanta, Georgia, USA, 7-10 December, 587-593.

J.T. Blake, M.W. Carter, and S. Richardson, 1996, An analysis of emergency room wait time issues via computer simulation. *INFOR* **34**(4):263-273.

R.E. Blasak, W.S. Armel, D.W. Starks, and M.C. Hayduk, 2003, The use of simulation to evaluate hospital operations between the emergency department and a medical telemetry unit, *Proceedings of the 2003 Winter Simulation Conference* (S. Chick, P.J. Sánchez, D. Ferrin, D.J. Morrice, Editors), Institute of Electrical and Electronics Engineers, New Orleans, Louisiana, USA, 7-10 December, 1887-1893.

K. Bodtker, L. Wilson, and W. Godolphin, 1992, Simulation as an aid to clinical chemistry laboratory planning, *Proceedings of the 1992 Conference on Simulation in Health Care and Social Services* (J. Anderson, Editor), Newport Beach, California, USA, 20-22 January, 15-18.

T. Butler, G. Reeves, K. Karwan, and J. Sweigart, 1992a, Assessing the impact of patient care policies using simulation analysis, *Journal of the Society for Health Systems*, **3**(3):38-53.

T.W. Butler, K.R. Karwan, and J.R. Sweigart, 1992b, Multi-level strategic evaluation of hospital plans and decisions, *Journal of the Operational Research Society*, **43**(7):665-675.

T.W. Butler, K.R. Karwan, J.R. Sweigart, and G.R. Reeves, 1992c, An integrative model-based approach to hospital layout, *IIE Transactions*, **24**(2):144-152.

W. Cahill and M. Render, 1999, Dynamic simulation modeling of ICU bed availability, *Proceedings of the 1999 Winter Simulation Conference* (P.A. Farrington, H.B. Nembhard, D.T. Sturrock, G.W. Evans, Editors), Institute of Electrical and Electronics Engineers, Phoenix, Arizona, USA, 5-8 December, 1573-1576.

R.C. Carlson, J.C. Hershey, and D.H. Kropp, 1979, Use of optimization and simulation models to analyze outpatient health care settings, *Decision Sciences*, **10**:412-433.

D. Carroll, 1996, MedModel-Healthcare simulation software, *Proceedings of the 1996 Winter Simulation Conference* (J.M. Charnes, D.M. Morrice, D.T. Brunner, J.J. Swain, Editors), Institute of Electrical and Electronics Engineers, Coronado, California, USA, 8-11 December, 441-446.

J.S. Carson, 1996, AutoStat output statistical analysis for AutoMod Users, *Proceedings of the 1996 Winter Simulation Conference* (J.M. Charnes, D.M. Morrice, D.T. Brunner, J.J. Swain, Editors), Institute of Electrical and Electronics Engineers, Coronado, California, USA, 8-11 December, 492-499.

Y. Carson and A. Maria, 1997, Simulation optimization: Methods and applications, *Proceedings of the 1997 Winter Simulation Conference* (S. Andradottir, K.J. Healy, D.E. Withers, B.L. Nelson, Editors), Institute of Electrical and Electronics Engineers, Atlanta, Georgia, USA, 7-10 December, 118-126.

M.W. Carter, L.L. O'Brien-Pallas, J.T. Blake, L.McGillis, and S. Zhu, 1992, Simulation, scheduling, and operating rooms, *Proceedings of the 1992 Simulation in Health Care and Social Services Conference* (J.G. Anderson, Editor), Simulation Council Inc., San Diego, California, USA, 28-30.

M.A. Centeno, C. Albacete, D.O. Terzano, M. Carrillo, and T. Ogazon, 2000, A simulation study of the radiology department at JMH, *Proceedings of the 2000 Winter Simulation Conference* (J.A. Joines, R.R. Barton, K. Kang, P.A. Fishwick, Editors), Institute of Electrical and Electronics Engineers, Orlando, Florida, USA, 10-13 December, 1978-1984.

M.A. Centeno, R. Giachetti, R. Linn, and A.M. Ismail, 2003, A simulation-ILP based tool for scheduling ER staff, *Proceedings of the 2003 Winter Simulation Conference* (S. Chick, P.J. Sánchez, D. Ferrin, D.J. Morrice, Editors), Institute of Electrical and Electronics Engineers, New Orleans, Louisiana, USA, 7-10 December, 1930-1938.

M.A. Centeno, M.A. Lee, E. Lopez, H.R. Fernandez, M. Carrillo, and T. Ogazon, 2001, A simulation study of the labor and delivery rooms and JMH, *Proceedings of the 2001 Winter Simulation Conference* (B.A. Peters, J.S. Smith, D.J. Medeiros, M.W. Rohrer, Editors), Institute of Electrical and Electronics Engineers, Arlington, Virginia, USA, 9-12 December, 1392-1400.

S.-Y.E. Chan, J. Ohlmann, S. Dunbar, C. Dunbar, S. Ryan, and P. Savory, 2002, Operations research methods applied to workflow in a medical records department, *Health Care Management Science*, **5**:191-199.

M.A. Coffin, G. Lassiter, B. Killingsworth, and J.W. Kleckley, 1993, A simulation model of an X-ray facility, *1993 SCS Western Multiconference on Simulation: Simulation in the Health Sciences and Services* (J.G. Anderson, M. Katzper, Editors), Society for Computer Simulation, La Jolla, California, USA, 17-20 January, 3-7.

M.A. Cohen, J.C. Hershey, and E.N. Weiss, 1980, Analysis of capacity decisions for progressive patient care hospital facilities, *Health Services Research*, **15**:145-160.

K. Currie, W. Iskander, L. Michael, and C. Coberly, 1984, Simulation modeling in health care facilities, *Proceedings of the 1984 Winter Simulation Conference* (S. Sheppard, U.W. Pooch, C.D. Pegden, Editors), Institute of Electrical and Electronics Engineers, Dallas, Texas, USA, 28-30 November, 713-717.

R. Davies and H. Davies, 1994, Modeling patient flows and resource provision in health systems, *Omega*, **22**(2):123-131.

B. Dean, A. van Ackere, S. Gallivan, and N. Barber, 1999, When should pharmacists visit their wards? An application of simulation to planning hospital pharmacy services, *Health Care Management Science*, **2**:35-42.

D. Dearie, J. Gerson, and T. Warfield, 1976, The development and use of a simulation model of an outpatient clinic, *Proceedings of the 1976 Summer Computer Simulation Conference*, Simulation Council, Washington, DC, USA, 12-14 July, 554-558.

M.A. Draeger, 1992, An emergency department simulation model used to evaluate alternative nurse staffing and patient population scenarios, *Proceedings of the 1992 Winter Simulation Conference* (J.J. Swain, D. Goldsman, R.C. Crain, J.R. Wilson, Editors),

Institute of Electrical and Electronics Engineers, Arlington, Virginia, USA, 13-16 December, 1057-1064.

M.C. Drevna and C.J. Kasales, 1984, Introduction to Arena, *Proceedings of the 1984 Winter Simulation Conference* (S. Sheppard, U.W. Pooch, C.D. Pegden, Editors), Institute of Electrical and Electronics Engineers, Dallas, Texas, USA, 28-30 November, 431-436.

M.B. Dumas, 1984, Simulation modeling for hospital bed planning, *Simulation*, **43**:69-78.

M.B. Dumas, 1985, Hospital bed utilization: An implemented simulation approach to adjusting and maintaining appropriate levels, *Health Services Research*, **20**(1): 43-61.

R. Edwards, J. Clague, J. Barlow, M. Clarke, P. Reed, and R. Rada, 1994, Operations research survey and computer simulation of waiting times in two medical outpatient clinic structures, *Health Care Analysis*, **2**:164-169.

J. El-Darzi, C. Vasilakis, T. Chaussalet, and P.H. Millard, 1998, A simulation modeling approach to evaluating length of stay, occupancy, emptiness, and bed blocking in a hospital geriatric department, *Health Care Management Science*, **1**:143-149.

T. Eldabi and R.J. Paul, 2001, A proposed approach for modeling healthcare systems for understanding, *Proceedings of the 2001 Winter Simulation Conference* (B.A. Peters, J.S. Smith, D.J. Medeiros, M.W. Rohrer, Editors), Institute of Electrical and Electronics Engineers, Arlington, Virginia, USA, 9-12 December, 1412-1420.

W. England and S. Roberts, 1978, Applications of computer simulation in health care, *Proceedings of the 1978 Winter Simulation Conference* (H.J. Highland, L.G. Hull, N.R. Neilsen, Editors), Institute of Electrical and Electronics Engineers, Miami Beach, Florida, USA, 4-6 December, 665-676.

G.W. Evans, T.B. Gor, and E. Unger, 1996, A simulation model for evaluating personnel schedules in a hospital emergency department, *Proceedings of the 1996 Winter Simulation Conference* (J.M. Charnes, D.M. Morrice, D.T. Brunner, J.J. Swain, Editors), Institute of Electrical and Electronics Engineers, Coronado, California, USA, 8-11 December, 1205-1209.

J.E. Everett, 2002, A decision support simulation model for the management of an elective surgery waiting system, *Health Care Management Science*, **5**:89-95.

D.M. Ferrin, M.J. Miller, S. Wininger, and M.S. Neuendorf, 2004, Analyzing incentives and scheduling in a major metropolitan hospital operating room through simulation, *Proceedings of the 2004 Winter Simulation Conference* (R.G. Ingalls, M.D. Rossetti, J.S. Smith, B.A. Peters, Editors), Institute of Electrical and Electronics Engineers, Washington, D.C., USA, 5-8 December, 1975-1980.

R.B. Fetter and J.D. Thompson, 1965, The simulation of hospital systems, *Operations Research*, **13**(5): 689-711.

K.E. Fitzpatrick, J.R. Baker, and D.S. Dave, 1993, An application of computer simulation to improve scheduling of hospital operating room facilities in the United States, *International Journal of Computer Applications in Technology*, **6**(4):215-224.

R.W. Freedman, 1994, Reduction of average length of stay in the emergency room using discrete simulation, *Proceedings of Simulation in the Health Sciences* (J.G. Anderson, M. Katzper, Editors), Society for Computer Simulation, Tempe, Arizona, USA, 24-26 January, 6-8.

S.C. Gabaeff and J. Lennon, 1991, New computerized technology for the design and planning of emergency departments, *Proceedings of the American Hospital Association*, American Hospital Association, Anaheim, California, USA, July, 1-15.

M.L. Garcia, M.A. Centeno, C. Rivera, and N. DeCario, 1995, Reducing time in an emergency room via a fast-track, *Proceedings of the 1995 Winter Simulation Conference*

(C. Alexopoulos, K. Kang, W.R. Lilegdon, D. Goldsman, Editors), Institute of Electrical and Electronics Engineers, Washington DC, USA, 3-6 December, 1048-1053.

P.J. Gipps, 1986, The role of computer graphics in validating simulation models, *Mathematics and Computers in Simulation*, **28**(4): 285-289.

F. Glover, J.P. Kelly, and M.L. Laguna, 1996, New advances and applications of combining simulation and optimization, *Proceedings of the 1996 Winter Simulation Conference* (J.M. Charnes, D.M. Morrice, D.T. Brunner, J.J. Swain, Editors), Institute of Electrical and Electronics Engineers, Coronado, California, USA, 8-11 December, 144-152.

W. Godolphin, K. Bodtker, and L. Wilson, 1992, Simulation modeling: A tool to help predict the impact of automation in clinical laboratories, *Laboratory Robotics and Automation*, **4**(5): 249-255.

M. Goitein, 1990, Waiting patiently, *The New England Journal of Medicine*, **323**(9): 604-608.

S. Groothuis, H.M.J. Goldschmidt, E.J. Drupsteen, J.C.M. de Vries, A. Hasman, and G.G. van Merode, 2002, Application of computer simulation analysis to assess the effects of relocating a hospital phlebotomy department, *Annals of Clinical Biochemistry*, **39**:261-272.

S. Groothuis, G.G. van Merode, and A. Hasman, 2001, Simulation as decision tool for capacity planning, *Computers Methods and Programs in Biomedicine*, **66**:139-151.

M. Guo, M. Wagner, and C. West, 2004, Outpatient clinic scheduling—A simulation approach, *Proceedings of the 2004 Winter Simulation Conference* (R.G. Ingalls, M.D. Rossetti, J.S. Smith, B.A. Peters, Editors), Institute of Electrical and Electronics Engineers, Washington, D.C., USA, 5-8 December, 1981-1987.

W.M. Hancock, D.B. Magerlein, R.H. Storer, and J.B. Martin, 1978, Parameters affecting hospital occupancy and implications for faculty sizing, *Health Services Research*, **13**:276-289.

W. Hancock and P. Walter, 1979, The use of computer simulation to develop hospital systems, *Simuletter*, **10**(4): 28-32.

W. Hancock and P. Walter, 1984, The use of admissions simulation to stabilize ancillary workloads, *Simulation*, **43**(2): 88-94.

P.R. Harper, 2002, A framework for operational modelling of hospital resources, *Health Care Management Science*, **5**:165-173.

C.R. Harrell and R.N. Price, 2000, Healthcare simulation modeling and optimization using MEDMODEL, *Proceedings of the 2000 Winter Simulation Conference* (J.A. Joines, R.R. Barton, K. Kang, P.A. Fishwick, Editors), Institute of Electrical and Electronics Engineers, Orlando, Florida, USA, 10-13 December, 203-207.

C.R. Harrell and V.R. Lange, 2001, Healthcare simulation modeling and optimization using MEDMODEL. *Proceedings of the 2001 Winter Simulation Conference* (B.A. Peters, J.S. Smith, D.J. Medeiros, M.W. Rohrer, Editors), Institute of Electrical and Electronics Engineers, Arlington, Virginia, USA, 9-12 December, 233-238.

R.A. Harris, 1985, Hospital bed requirements planning, *European Journal of Operational Research*, **25**:121-126.

F. Hashimoto and S. Bell, 1996, Improving outpatient clinic staffing and scheduling with computer simulation, *Journal of General Internal Medicine*, **11**:182-184.

D.L. Heflin and C.R. Harrell, 1998, Healthcare simulation modeling and optimization using MEDMODEL, *Proceedings of the 1998 Winter Simulation Conference* (J.D. Medeiros, E.F. Watson, J.S. Carson, M.S. Manivannan, Editors), Institute of Electrical and Electronics Engineers, Washington, D.C., USA, 13-16 December, 185-190.

K. Ishimoto, T. Ishimitsu, A. Koshiro, and S. Hirose, 1990, Computer simulation of optimum personnel assignment in hospital pharmacy using a work-sampling method, *Medical Informatics*, **15**(4): 343-354.

W.H. Iskander and D.M. Carter, 1991, A simulation model for a same day care facility at a university hospital, *Proceedings of the 1991 Winter Simulation Conference* (B.L. Nelson, W.D. Kelton, G.M. Clark, Editors), Institute of Electrical and Electronics Engineers, Phoenix, Arizona, USA, 8-11 December, 846-853.

M.W. Isken, T.J. Ward, and T.C. McKee, 1999, Simulating outpatient obstetrical clinics, *Proceedings of the 1999 Winter Simulation Conference* (P.A. Farrington, H.B. Nembhard, D.T. Sturrock, G.W. Evans, Editors), Institute of Electrical and Electronics Engineers, Phoenix, Arizona, USA, 5-8 December, 1557-1563.

W.C. Johnson, 1998, Birth of a new maternity process, *Proceedings of the 1998 Winter Simulation Conference* (J.D. Medeiros, E.F. Watson, J.S. Carson, M.S. Manivannan, Editors), Institute of Electrical and Electronics Engineers, Washington, D.C., USA, 13-16 December, 1429-1432.

L.M. Jones and A.J. Hirst, 1986, Visual simulation in hospitals: A managerial or a political tool? *European Journal of Operational Research*, **29**:167-177.

J.B. Jun, S.H. Jacobson, and J.R. Swisher, 1999, Applications of discrete-event simulation in health care clinics: A survey, *Journal of the Operational Research Society*, **50**(2): 109-123.

S.K. Kachhal, G.A. Klutke, and E.B. Daniels, 1981, Two simulation applications to outpatient clinics, *Proceedings of the 1981 Winter Simulation Conference* (T.I. Oren, C.M. Delfosse, C.M. Shubl, Editors), Institute of Electrical and Electronics Engineers, Atlanta, Georgia, USA, 9-11 December, 657-665.

D. Kanon, 1974, Simulation of waiting line problems in a hospital setting, *Proceedings of the 1st World Conference on Medical Information* (J. Anderson, J.M. Forsythe, Editors), North-Holland, Stockholm, Netherlands, 5-10 August, 503-507.

J. Karnon, 2003, Alternative decision modelling techniques for the evaluation of health care technologies: Markov processes versus discrete-event simulation, *Health Economics*, **12**: 837-848.

L.F. Keller, 1994, MedModel-Specialized software for the healthcare industry, *Proceedings of the 1994 Winter Simulation Conference* (J.D. Tew, S. Manivannan, D.A. Sadowski, A.F. Seila, Editors), Institute of Electrical and Electronics Engineers, Lake Buena Vista, Florida, USA, 11-14 December, 533-537.

J.W. Kho and G.M. Johnson, 1976, Computer simulation of a hospital health-care delivery system, *Proceedings of the 1976 Bicentennial Winter Simulation Conference* (R.G. Sargent, H.J. Highland, T.J. Schriber, Editors), Institute of Electrical and Electronics Engineers, Gaithersburg, Maryland, USA, 6-8 December, 349-360.

A. Kirtland, J. Lockwood, K. Poisker, L. Stamp, and P. Wolfe, 1995, Simulating an emergency department is as much fun as..., *Proceedings of the 1995 Winter Simulation Conference*, (C. Alexopoulos, K. Kang, W.R. Lilegdon, D. Goldsman, Editors), Institute of Electrical and Electronics Engineers, Washington DC, USA, 3-6 December, 1039-1042.

K.A. Klafehn, 1987, Impact points in patient flows through a radiology department provided through simulation, *Proceedings of the 1987 Winter Simulation Conference* (A Thesen, H Grant, WD Kelton, Editors), Institute of Electrical and Electronics Engineers, Atlanta, Georgia, USA, 14-16 December, 914-918.

K.A. Klafehn and M. Connolly, 1993, The simulation/animation of a new outpatient hematology laboratory, *1993 SCS Western Multiconference on Simulation: Simulation in the Health Sciences and Services* (J.G. Anderson, M. Katzper, Editors), Society for Computer Simulation, La Jolla, California, USA, 17-20 January, 12-15.

K.A. Klafehn and D. Owens, 1987, A simulation model designed to investigate resource utilization in a hospital emergency room, *Proceedings of the Eleventh Annual Symposium*

on Computer Applications in Medical Care (W. Stead, Editor), Institute of Electrical and Electronics Engineers, Washington DC, USA, 1-4 November, 676-679.

K.A. Klafehn, D. Owens, R. Felter, N. Vonneman, and C. McKinnon, 1989, Evaluating the linkage between emergency medical services and the provision of scarce resources through simulation, *Proceedings of the 13th Annual Symposium on Computer Applications in Medical Care* (L. Kingsland III, Editor), Institute of Electrical and Electronics Engineers, Washington DC, USA, 5-8 November, 335-339.

K.J. Klassen and T.R. Rohleder, 1996, Scheduling outpatient appointments in a dynamic environment, *Journal of Operations Management*, **14**:83-101.

R.W. Klein, R.S. Dittus, S.D. Roberts, and J.R. Wilson, 1993, Simulation modeling and health-care decision making, *Medical Decision Making*, **13**(4):347-354.

M.G. Kletke and T.E. Dooley, 1984, A simulation model of a maternity ward: A key planning tool for hospital administrators, *Proceedings of the Conference on Simulation in Health Care Delivery System*, San Diego, California, USA, 2-4 February, 35-39.

M.J. Kraitsik and A. Bossmeyer, 1993, Simulation applied to planning an emergency department expansion, *1993 SCS Western Multiconference on Simulation: Simulation in the Health Sciences and Services* (J.G. Anderson, M. Katzper, Editors), Society for Computer Simulation, La Jolla, California, USA, 17-20 January, 19-27.

D. Kropp, R.C. Carlson, and J.V. Jucker, 1978, Use of both optimization and simulation models to analyze complex systems, *Proceedings of the 1978 Winter Simulation Conference* (H.J. Highland, L.G. Hull, N.R. Neilsen, Editors), Institute of Electrical and Electronics Engineers, Miami Beach, Florida, USA, 4-6 December, 195-201.

D. Kropp and J. Hershey, 1979, Recursive optimization-simulation modeling for the analysis of ambulatory health care facilities, *Simuletter*, **10**(4): 43-46.

A.P. Kumar and R. Kapur, 1989, Discrete simulation application-scheduling staff for the emergency room, *Proceedings of the 1989 Winter Simulation Conference* (E.A. MacNair, K.J. Musselman, P. Heidelberger, Editors), Institute of Electrical and Electronics Engineers, Washington DC, USA, 4-6 December, 1112-1120.

P.J. Kuzdrall, N.K. Kwak, and H.H. Schmitz, 1981, Simulating space requirements and scheduling policies in a hospital surgical suite, *Simulation*, **27**:163-171.

N. Kwak, P. Kuzdrall, and H. Schmitz, 1975, Simulating the use of space in a hospital surgical suite, *Simulation*, **24**(5): 147-152.

J.M. Lach and R.M. Vázquez, 2004, Simulation model of the telemedicine program, *Proceedings of the 2004 Winter Simulation Conference* (R.G. Ingalls, M.D. Rossetti, J.S. Smith, B.A. Peters, Editors), Institute of Electrical and Electronics Engineers, Washington, D.C., USA, 5-8 December, 2012-2017.

E. Lambo, 1983, An optimization-simulation model of a rural health center in Nigeria, *Interfaces*, **13**(3): 29-35.

A.M. Law and W.D. Kelton, 2000, *Simulation Modelling and Analysis*, 3rd Ed., McGraw-Hill.

B. Lehaney and V. Hlupic, 1995, Simulation modeling for resource allocation and planning in the health sector, *Journal of the Royal Society of Health*, **115**(6): 382-385.

B. Lehaney and R.J. Paul, 1994, Using soft systems methodology to develop a simulation of out-patient services, *Journal of the Royal Society for Health*, **114**:248-251.

B. Lehaney and R.J. Paul, 1996, The use of soft systems methodology in the development of a simulation of outpatient services at Watford General Hospital, *Journal of the Operational Research Society*, **47**:864-870.

J. Lennon, 1992, Simulation in the design and planning of emergency departments, *1992 SCS Western Multiconference: Simulation in education for business, management, and MIS*, Society for Computer Simulation, Newport Beach, California, USA, January, 93-97.

J.L. Levy, B.A. Watford, and V.T. Owen, 1989, Simulation analysis of an outpatient services facility, *Journal of the Society for Health Systems*, **1**(2): 35-49.

T. Lim, D. Uyeno, and I. Vertinsky, 1975, Hospital admissions systems: A simulation approach, *Simulation and Games*, **6**(2): 188-201.

L. Liyanage and M. Gale, 1995, Quality improvement for the Campbelltown hospital emergency service, *1995 IEEE International Conference on Systems, Man, and Cybernetics*, Institute of Electrical and Electronics Engineers, Vancouver, British Columbia, Canada, 22-25 October, 13: 1997-2002.

B.G. Lopez-Valcarcel and P.B. Perez, 1994, Evaluation of alternative functional designs in an emergency department by means of simulation, *Simulation*, **63**(1): 20-28.

J.C. Lowery, 1992, Simulation of a hospital's surgical suite and critical care area, *Proceedings of the 1992 Winter Simulation Conference* (J.J. Swain, D. Goldsman, R.C. Crain, J.R. Wilson, Editors), Institute of Electrical and Electronics Engineers, Arlington, Virginia, USA, 13-16 December, 1071-1078.

J.C. Lowery, 1993, Multi-hospital validation of critical care simulation model, *Proceedings of the 1993 Winter Simulation Conference* (G.W. Evans, M. Mollaghasemi, E.C. Russell, W.E. Biles, Editors), Institute of Electrical and Electronics Engineers, Los Angeles, California, USA, 12-15 December, 1207-1215.

J.C. Lowery, 1994, Barriers to implementing simulation in health care, *Proceedings of the 1994 Winter Simulation Conference* (J.D. Tew, S. Manivannan, D.A. Sadowski, A.F. Seila, Editors), Institute of Electrical and Electronics Engineers, Lake Buena Vista, Florida, USA, 11-14 December, 868-875.

J.C. Lowery, 1996, Introduction to simulation in health care, *Proceedings of the 1996 Winter Simulation Conference* (J.M. Charnes, D.M. Morrice, D.T. Brunner, J.J. Swain, Editors), Institute of Electrical and Electronics Engineers, Coronado, California, USA, 8-11 December, 78-84.

J.C. Lowery, 1998, Getting started in simulation healthcare, *Proceedings of the 1998 Winter Simulation Conference* (J.D. Medeiros, E.F. Watson, J.S. Carson, M.S. Manivannan, Editors), Institute of Electrical and Electronics Engineers, Washington, D.C., USA, 13-16 December, 31-35.

J.C. Lowery and J.A. Davis, 1999, Determination of operating room requirements using simulation, *Proceedings of the 1999 Winter Simulation Conference* (P.A. Farrington, H.B. Nembhard, D.T. Sturrock, G.W. Evans, Editors), Institute of Electrical and Electronics Engineers, Phoenix, Arizona, USA, 5-8 December, 1568-1572.

J.C. Lowery and J.B. Martin, 1992, Design and validation of a critical care simulation model, *Journal of the Society for Health Systems*, **3**(3): 15-36.

J.M. Magerlein and J.B. Martin, 1976, Surgical demand scheduling: A review, *Health Services Research*, **11**:53-68.

A. Mahachek, 1992, An introduction to patient flow simulation for health-care managers, *Journal of the Society for Health Systems*, **3**(3): 73-81.

A.R. Mahachek and T.L. Knabe, 1984, Computer simulation of patient flow in obstetrical/gynecology clinics, *Simulation*, **30**:95-101.

S. Mahapatra, C.P. Koelling, L. Patvivatsiri, B. Fraticelli, D. Eitel, and L. Grove, 2003, Pairing emergency severity index5-level triage data with computer aided system design to improve emergency department access and throughput, *Proceedings of the 2003 Winter Simulation Conference* (S. Chick, P.J. Sánchez, D. Ferrin, D.J. Morrice, Editors), Institute of Electrical and Electronics Engineers, New Orleans, Louisiana, USA, 7-10 December, 1917-1925.

J. Marsh, 1979, Simulation as a decision aid: A management perspective, *Simuletter*, **10**(5): 47-49.

E. Martin, R. Grønhaug, and K. Haugene, 2003, Proposals to reduce over-crowding, lengthy stays and improve patient care: Study on the geriatric department In Norway's largest hospital, *Proceedings of the 2003 Winter Simulation Conference* (S. Chick, P.J. Sánchez, D. Ferrin, D.J. Morrice, Editors), Institute of Electrical and Electronics Engineers, New Orleans, Louisiana, USA, 7-10 December, 1876-1881.

B.J. Masterson, T.G. Mihara, G. Miller, S.C. Randolph, M.E. Forkner, and A.L. Crouter, 2004, Using models and data to support optimization of the military health system: A case study in an intensive care unit, *Health Care Management Science*, **7**:217-224.

F. McGuire, 1994, Using simulation to reduce length of stay in emergency departments, *Proceedings of the 1994 Winter Simulation Conference* (J.D. Tew, S. Manivannan, D.A. Sadowski, A.F. Seila, Editors), Institute of Electrical and Electronics Engineers, Lake Buena Vista, Florida, USA, 11-14 December, 861-867.

M.L. McHugh, 1989, Computer simulation as a method for selecting nurse staffing levels in hospitals, *Proceedings of the 1989 Winter Simulation Conference* (E.A. MacNair, K.J. Musselman, P. Heidelberger, Editors), Institute of Electrical and Electronics Engineers, Washington DC, USA, 4-6 December, 1121-1129.

L. Meier, E. Sigal, and F.R. Vitale, 1985, The use of simulation model for planning ambulatory surgery, *Proceedings of the 1985 Winter Simulation Conference* (D.T. Gantz, G.C. Blais, S.L. Solomon, Editors), Institute of Electrical and Electronics Engineers, San Francisco, California, USA, 11-13 December, 558-563.

M.J. Miller, D.M. Ferrin, and M.G. Messer, 2004, Fixing the emergency department: A transformational journey with EDsim, *Proceedings of the 2004 Winter Simulation Conference* (R.G. Ingalls, M.D. Rossetti, J.S. Smith, B.A. Peters, Editors), Institute of Electrical and Electronics Engineers, Washington, D.C., USA, 5-8 December, 1988-1993.

M.J. Miller, D.M. Ferrin, and J.M. Szymanski, 2003, Simulating six sigma improvement ideas for a hospital emergency department, *Proceedings of the 2003 Winter Simulation Conference* (S. Chick, P.J. Sánchez, D. Ferrin, D.J. Morrice, Editors), Institute of Electrical and Electronics Engineers, New Orleans, Louisiana, USA, 7-10 December, 1926-1929.

B.P. Morrison and B.C. Bird, 2003, A methodology for modeling front office and patient care processes in ambulatory health care, *Proceedings of the 2003 Winter Simulation Conference* (S. Chick, P.J. Sánchez, D. Ferrin, D.J. Morrice, Editors), Institute of Electrical and Electronics Engineers, New Orleans, Louisiana, USA, 7-10 December, 1882-1886.

A.K. Mukherjee, 1991, A simulation model for management of operations in the pharmacy of a hospital, *Simulation*, **56**(2): 91-103.

D.R. Murphy and E. Sigal, 1985, Evaluating surgical block scheduling using computer simulation, *Proceedings of the 1985 Winter Simulation Conference* (D.T. Gantz, G.C. Blais, S.L. Solomon, Editors), Institute of Electrical and Electronics Engineers, San Francisco, California, USA, 11-13 December, 551-557.

P.C. O'Kane, 1981, A simulation model of a diagnostic radiology department, *European Journal of Operational Research*, **6**:38-45.

E. Olson and L.E. Dux, 1994, Computer model targets best route for expanding hospital surgicenter, *Industrial Engineering*, **26**(9): 24-6.

V.Z. Osidach and M.C. Fu, 2003, Computer simulation of a mobile examination center, *Proceedings of the 2003 Winter Simulation Conference* (S. Chick, P.J. Sánchez, D. Ferrin, D.J. Morrice, Editors), Institute of Electrical and Electronics Engineers, New Orleans, Louisiana, USA, 7-10 December, 1868-1875.

R.J. Paul, 1989, Visual simulation: Seeing is believing, *Impacts of Recent Computer Advances on Operations Research*, **9**:422-432.

R.J. Paul and J. Kuljis, 1995, A generic simulation package for organizing outpatient clinics, *Proceedings of the 1995 Winter Simulation Conference* (C. Alexopoulos, K. Kang, W.R. Lilegdon, D. Goldsman, Editors), Institute of Electrical and Electronics Engineers, Washington DC, USA, 3-6 December, 1043-1047.

R.N. Price and C.R. Harrell, 1999, Healthcare simulation modeling and optimization using MEDMODEL, *Proceedings of the 1999 Winter Simulation Conference* (P.A. Farrington, H.B. Nembhard, D.T. Sturrock, G.W. Evans, Editors), Institute of Electrical and Electronics Engineers, Phoenix, Arizona, USA, 5-8 December, 215-219.

J.S. Rakich, P.J. Kuzdrall, K.A. Klafehn, and A.G. Krigline, 1991, Simulation in the hospital setting: Implications for managerial decision making and management development, *Journal of Management Development*, **10**(4): 31-37.

S. Ramakrishnan, K. Nagarkar, M. DeGennaro, K. Srihari, A.K. Courtney, and F. Emick, 2004, A study of the CT scan Area of a healthcare provider, *Proceedings of the 2004 Winter Simulation Conference* (R.G. Ingalls, M.D. Rossetti, J.S. Smith, B.A. Peters, Editors), Institute of Electrical and Electronics Engineers, Washington, D.C., USA, 5-8 December, 2025-2031.

F.J. Ramis, J.L. Palma, and F.F. Baesler, 2001, The use of simulation for process improvement at an ambulatory surgery center, *Proceedings of the 2001 Winter Simulation Conference* (B.A. Peters, J.S. Smith, D.J. Medeiros, M.W. Rohrer, Editors), Institute of Electrical and Electronics Engineers, Arlington, Virginia, USA, 9-12 December, 1401-1404.

E.J Rising, R. Baron, and B. Averill, 1973, A systems analysis of a university-health-service outpatient clinic, *Operations Research*, **21**(5): 1030-1047.

M. Ritondo and R.W. Freedman, 1993, The effects of procedure scheduling on emergency room throughput: A simulation study, *1993 SCS Western Multiconference on Simulation: Simulation in the Health Sciences and Services* (J.G. Anderson, M. Katzper, Editors), Society for Computer Simulation, La Jolla, California, USA, 17-20 January, 8-11.

T.R. Rohleder and K.J. Klassen, 2002, Rolling horizon appointment scheduling: A simulation study, *Health Care Management Science*, **5**:201-209.

G. Romanin-Jacur and P. Facchin, 1987, Optimal planning of a pediatric semi-intensive care unit via simulation, *European Journal of Operational Research*, **29**:192-198

M.D. Rossetti, A. Kumar, and R.A. Felder, 1998, Mobile robot simulation of clinic laboratory deliveries, *Proceedings of the 1998 Winter Simulation Conference* (J.D. Medeiros, E.F. Watson, J.S. Carson, M.S. Manivannan, Editors), Institute of Electrical and Electronics Engineers, Washington, D.C., USA, 13-16 December, 1415-1421.

M.D. Rossetti, G.F. Trzcinski, and S.A. Syverud, 1999, Emergency department simulation and determination of optimal attending physician staffing schedules, *Proceedings of the 1999 Winter Simulation Conference* (P.A. Farrington, H.B. Nembhard, D.T. Sturrock, G.W. Evans, Editors), Institute of Electrical and Electronics Engineers, Phoenix, Arizona, USA, 5-8 December, 1532-1540.

S. Samaha, W.S. Armel, and D.W. Starks, 2003, The use of simulation to reduce the length of stay in an emergency department, *Proceedings of the 2003 Winter Simulation Conference* (S. Chick, P.J. Sánchez, D. Ferrin, D.J. Morrice, Editors), Institute of Electrical and Electronics Engineers, New Orleans, Louisiana, USA, 7-10 December, 1907-1911.

S.M. Sanchez, T. Ogazon, D.M. Ferrin, J.A. Sepúlveda, and T.J. Ward, 2000, Emerging issues in healthcare simulation, *Proceedings of the 2000 Winter Simulation Conference*

(J.A. Joines, R.R. Barton, K. Kang, P.A. Fishwick, Editors), Institute of Electrical and Electronics Engineers, Orlando, Florida, USA, 10-13 December, 1999-2003.

R.G. Sargent, 1992, Validation and verification of simulation models, *Proceedings of the 1992 Winter Simulation Conference* (J.J. Swain, D. Goldsman, R.C. Crain, J.R. Wilson, Editors), Institute of Electrical and Electronics Engineers, Arlington, Virginia, USA, 13-16 December, 104-114.

J.A. Sepúlveda, W.J. Thompson, F.F. Baesler, M.I. Alvarez, and L.E. Cahoon, III, 1999, The use of simulation for process improvement in a cancer treatment center, *Proceedings of the 1999 Winter Simulation Conference* (P.A. Farrington, H.B. Nembhard, D.T. Sturrock, G.W. Evans, Editors), Institute of Electrical and Electronics Engineers, Phoenix, Arizona, USA, 5-8 December, 1541-1548.

D. Sinreich and Y.N. Marmor, 2004, A simple and intuitive simulation tool for analyzing emergency department operations, *Proceedings of the 2004 Winter Simulation Conference* (R.G. Ingalls, M.D. Rossetti, J.S. Smith, B.A. Peters, Editors), Institute of Electrical and Electronics Engineers, Washington, D.C., USA, 5-8 December, 1994-2002.

S.R. Smith, B.J. Schroer, and R.E. Shannon, 1979, Scheduling of patients and resources for ambulatory health care, *Proceedings of the 1979 Winter Simulation Conference* (H.J. Highland, M.G. Spiegel, R. Shannon, Editors), Institute of Electrical and Electronics Engineers, San Diego, California, USA, 3-5 December, 553-562.

E.A Smith and H.R. Warner, 1971, Simulation of a multiphasic screening procedure for hospital admissions, *Simulation*, **17**(2): 57-64.

V.L. Smith-Daniels, S.B. Schweikhart, and D.E. Smith-Daniels, 1988, Capacity management in health care services: Review and future research directions, *Decision Sciences*, **19**:889-918.

E.F. Stafford, Jr, 1976, A General Simulation Model for Multifacility Outpatient Clinics, M.S. Thesis, Pennsylvania State University, Pennsylvania.

E.F. Stafford, Jr., 1978, Simulation vs. mathematical analysis for systems modeling: a comparison of techniques, *Proceedings of the 1978 Summer Computer Simulation Conference*, AFIPS Press, Los Angeles, California, USA, 24-26 July, 53-159.

J.E. Stahl, M.S. Roberts, and S. Gazelle, 2003, Optimizing management and financial performance of the teaching ambulatory care clinic, *Journal of General Internal Medicine*, **18**:266-274.

C.R. Standridge, 1999, A tutorial on simulation in health care: Applications and issues, *Proceedings of the 1999 Winter Simulation Conference* (P.A. Farrington, H.B. Nembhard, D.T. Sturrock, G.W. Evans, Editors), Institute of Electrical and Electronics Engineers, Phoenix, Arizona, USA, 5-8 December, 49-55.

D. Steward and C.R. Standridge, 1996, A veterinary practice simulator based on the integration of expert system and process modeling, *Simulation*, **66**:143-159.

J.R. Swisher and S.H. Jacobson, 2002, Evaluating the design of a family practice healthcare clinic using discrete-event simulation, *Health Care Management Science*, **5**:75-88.

J.R. Swisher, B.J. Jun, S.H. Jacobson, and O. Balci, 1997, Simulation of the Queston physician network, *Proceedings of the 1997 Winter Simulation Conference* (S. Andradottir, K.J. Healy, D.E. Withers, B.L. Nelson, Editors), Institute of Electrical and Electronics Engineers, Atlanta, Georgia, USA, 7-10 December, 1146-1154.

J.R. Swisher, S.H. Jacobson, J.B. Jun, and O. Balci, 2001, Modeling and analyzing a physician clinic environment using discrete-event (visual) simulation, *Computers and Operations Research*, **28**(2): 105-125.

S.T. Takakuwa and H. Shiozaki, 2004, Functional analysis for operating emergency department of a general hospital, *Proceedings of the 2004 Winter Simulation Conference*

(R.G. Ingalls, M.D. Rossetti, J.S. Smith, B.A. Peters, Editors), Institute of Electrical and Electronics Engineers, Washington, D.C., USA, 5-8 December, 2003-2011.

B.A. Tan, A. Gubaras, and N. Phojanamongkolkij, 2002, Simulation study of Dreyer urgent care facility, *Proceedings of the 2002 Winter Simulation Conference* (E. Yücesan, C.H. Chen, J.L. Snowdon, J.M. Charnes, Editors), Institute of Electrical and Electronics Engineers, San Diego, California, USA, 8-11 December, 1922-1927.

D. Valinsky, 1975, Simulation, *Operations Research in Healthcare: A Critical Analysis* (L.J. Shuman, R.D. Speas, J.P. Young, Editors), The Johns Hopkins University Press: Baltimore, Maryland, USA.

C. Vasilakis and E. El-Darzi, 2001, A simulation study of the winter bed crisis, *Health Care Management Science*, **4**:31-36.

G. Vassilacopoulos, 1985, A simulation model for bed allocation to hospital inpatient departments, *Simulation*, **45**(5): 233-241.

S. Vemuri, 1984, Simulated analysis of patient waiting time in an outpatient pharmacy, *American Journal of Hospital Pharmacy*, **41**:1127-1130.

J.M.H. Vissers, 1998, Health care management modelling: A process perspective, *Health Care Management Science*, **1**:77-85.

S.D. Walter, 1973, A comparison of appointment schedules in hospital radiology department, *British Journal of Preventive and Social Medicine*, **27**:160-167.

M.L. Weng and A.A. Houshmand, 1999, Healthcare simulation: A case study at a local clinic, *Proceedings of the 1999 Winter Simulation Conference* (P.A. Farrington, H.B. Nembhard, D.T. Sturrock, G.W. Evans, Editors), Institute of Electrical and Electronics Engineers, Phoenix, Arizona, USA, 5-8 December, 1577-1584.

A. Wiinamaki and R. Dronzek, 2003, Using simulation in the architectural concept phase of an emergency department design, *Proceedings of the 2003 Winter Simulation Conference* (S. Chick, P.J. Sánchez, D. Ferrin, D.J. Morrice, Editors), Institute of Electrical and Electronics Engineers, New Orleans, Louisiana, USA, 7-10 December, 1912-1916.

S.V. Williams, 1983, How many intensive care beds are enough? *Critical Care Medicine*, **11**(6): 412-416.

W.J. Williams, R.P. Covert, and J.D. Steele, 1967, Simulation modeling of a teaching hospital clinic, *Hospitals*, **41**(21): 71-75.

J.C.T. Wilson, 1981, Implementation of computer simulation projects in health care, *Journal of the Operational Research Society*, **32**:825-832.

A. Wilt and D. Goddin, 1989, Health care case study: Simulating staffing needs and work flow in an outpatient diagnostic center, *Industrial Engineering*, **21**(5): 22-26.

C. Wong, G. Geiger, Y.D. Derman, C.R. Busby, and M.W. Carter, 2003, Redesigning the medication ordering, dispensing, and administration process in an acute care academic health sciences centre. *Proceedings of the 2003 Winter Simulation Conference* (S. Chick, P.J. Sánchez, D. Ferrin, D.J. Morrice, Editors), Institute of Electrical and Electronics Engineers, New Orleans, Louisiana, USA, 7-10 December, 1894-1902.

M.B. Wright, 1987, The application of a surgical bed simulation model, *European Journal of Operational Research*, **32**:26-32.

F. Zilm, D. Arch, and R.B. Hollis, 1983, An application of simulation modeling to surgical intensive care bed need analysis in a university hospital, *Hospital & Health Services Administration*, **28**(5): 82-101.