Application of Discrete-Event Simulation in Health Care Clinics: A Survey

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Application of discrete-event simulation in health care clinics: A survey

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In recent decades, health care costs have dramatically increased, while health care organisations have been under severe pressure to provide improved quality health care for their patients. Several health care administrators have used discrete-event simulation as an effective tool for allocating scarce resources to improve patient flow, while minimising health care delivery costs and increasing patient satisfaction. The rapid growth in simulation software technology has created numerous new application opportunities, including more sophisticated implementations, as well as combining optimisation and simulation for complex integrated facilities. This paper surveys the application of discrete-event simulation modeling to health care clinics and systems of clinics (for example, hospitals, outpatient clinics, emergency departments, and pharmacies). Future directions of research and applications are also discussed.

Keywords: simulation; health services; hospitals; clinics

Introduction

Over the past thirty years, the dramatic increase in the cost of health care has compelled researchers and health care professionals to examine new ways to improve efficiency and reduce costs. Discrete-event simulation is one tool available to health care decision-makers that can assist in this endeavor. Discrete-event simulation is an operational research technique that allows the end user (namely, hospital administrators or clinic managers) to assess the efficiency of existing health care delivery systems, to ask ‘what if?’ questions, and to design new systems. Discrete-event simulation can also be used to forecast the impact of changes in patient flow, to examine resource needs (either in staffing or in physical capacity), or to investigate the complex relationships among the different model variables (for example, rate of arrivals or rate of service). This information allows managers to select management alternatives that can be used to reconfigure existing systems, to improve system performance or design, and to plan new systems, without altering the present system.

In recent years, the application of discrete-event simulation in health care has become increasingly wide spread. This may be attributed to the numerous successful studies reported using simulation to address health care system problems and the ever-increasing sophistication of simulation software packages. To gain a better appreciation for how extensively discrete-event simulation has been used to address health care clinic problems, a survey of the literature was conducted. Future health care planners, management engineers, as well as researchers will benefit from this study, by having ready access to an up-to-date, comprehensive collection of articles describing these applications. Moreover, suggestions for future opportunities and future needs in this area will be identified and discussed.

This paper focuses on articles that analyse single or multi-facility health care clinics (for example, outpatient clinics, emergency departments, surgical centers, orthopedic departments, and pharmacies). Interestingly, there are very few articles that report on using simulation to study complex integrated systems. This may be due to the extensive data requirements that are needed to support such studies, and the prohibitive expenses associated with such a data collection.

An extensive taxonomy of the literature over the past twenty years is presented (though some relevant earlier articles are also referenced). Simulation studies on wide area or regional health care community planning, ambulance location services, gurney transportation, disease control planning, and studies that do not address some aspects of patient flow are not discussed. For a complete review of the literature in health care prior to the mid-seventies, see England and Roberts[1] and Valinsky.[2]

Several review papers[1–4] and tutorials[5–8] have been written on conducting a simulation study in health care clinics. England and Roberts[1] gave an excellent comprehensive survey on the application of simulation in twenty-one health care areas (including laboratory studies, emergency services, and the national health care system). They cite ninety-two simulation models out of twelve hundred models reviewed, including all published models developed

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through 1978. Klein *et al*[3] presented a bibliography that includes operational decision making, medical decision making, and system dynamics planning models. Smith-Daniels *et al*[4] reviewed the literature pertaining to acquisition decisions (for example, facility location, aggregate capacity, and sizing of facility) and allocation decisions (for example, inpatient admissions scheduling, surgical facility scheduling, and ambulatory care scheduling). Their reviews include several operational research methodologies, such as heuristics, Markov chains, linear programming, and queuing theory, as well as simulation.

Banks and Carson[5] and Mahachek[6] provide tutorials on the steps required when conducting a health care system simulation study. Mahachek also provides details of a simulation study on hospital patient flow. Kanon[7] showed the relative ease with which one could use sample data to build a simulation model of a simplified problem in a hospital setting. Lowery[8] discussed some of the issues facing an analyst when using simulation to study a health care system, such as degree of model complexity, definition of input distributions, model validation, and interpretation of findings. All these articles provide useful information for practitioners interested in using discrete-event simulation to study health care systems and issues. Moreover, the articles focus on a common theme, namely the unique factors inherent in health care systems, and how simulation can be used to address such systems.

This paper is organised as follows: the first section presents the impact of patient scheduling and admissions, patient flow schemes, and staff scheduling on patient flow and work flow. The following section examines the allocation of resources when sizing and planning beds, rooms, and staff personnel. The next section discusses the lack of complex integrated multi-facility systems, advances in visual simulation, use of both simulation and optimisation techniques, and issues of implementation. Finally, a summary of simulation modeling in health care clinics is presented.

Patient flow

Hospitals and clinics are facing increasing competition for their services. To attract new patients and retain their patronage, hospitals and clinics must be able to provide fast and efficient health care. Effective and efficient patient flow is indicated by high patient throughput, low patient waiting times, a short length of stay at the clinic, and low clinic overtime, while maintaining adequate staff utilisation rates and low physician idle times. Three areas that impact patients in clinics are:

(i) patient scheduling and admissions,
(ii) patient routing and flow schemes,
(iii) scheduling and availability of resources.

Each of these three issues will now be looked at in greater depth.

Patient scheduling and admissions

Patient scheduling and admissions focus on procedures that determine how patient appointments (with medical staff) are scheduled, both in terms of when and how they are set in a given day, and their length of time. More specifically, this involves rules that determine when appointments can be made (namely, morning *vs* afternoon) and the length (spacing) of time between appointments. This may also be extended to include designating the specific type of medical staff who will be responsible for treating patients and the clinic space that will be required to deliver the necessary treatments. These issues can have a significant impact on how resources (for example, physicians, staff, or facilities) can be optimally utilised so as to maximise patient flow (hence increase profitability) without incurring additional costs of excessive patient waiting.

Most simulation studies that focus on patient scheduling and admissions are for outpatient clinics. Fetter and Thompson[9] presented results of one of the earliest simulation studies conducted in the area of individual clinical facility operations for outpatient clinics. They analysed the physician utilisation rate 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 determined that if the physician appointments increase from 60% to 90% (capacity), the physician idle time decreases by 160 hours and patient waiting time increases by 1600 hours (over a fifty day period). If this capacity increase were to be implemented, the simulation study suggested 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.

Evenly distributing patient demand has been used to improve patient throughput and patient waiting times in outpatient clinics. Smith and Warner[10] compared the case when patients arrive according to a uniform arrival pattern *vs* patient arrival patterns that are highly variable. They showed that the uniform arrival pattern can decrease the average length of stay at the clinic by over 40% (from 40.6 minutes to 24 minutes). Similarly, Rising *et al*[11] increased the number of appointment slots in an outpatient clinic on those days that had the least number of walk-ins, thereby smoothing demand on the physician. Their results show a 13.4% increase in patient throughput and less clinic overtime. Kho and Johnson[12] and Kachhal *et al*[13] showed 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, alternative scheduling rules have also been investigated. Bailey[14] developed an outpatient clinic scheduling rule that yields acceptable results for both patients (in terms of waiting times) and staff (in terms of utilisation), assuming that all patients have the same service time distributions and that all patients arrive punctually (that is, at their designated times). The rule schedules two patients at the beginning of every session (morning or afternoon), with all other patients scheduled at equal intervals. In a similar study, Smith *et al*[15] used a modified-wave scheduling scheme for an outpatient clinic to find the maximum number of patients a physician could see while minimising patient waiting time. This scheme schedules more patients 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. They showed that this schedule was superior to the uniform scheduling scheme, in terms of patient flow and patient waiting times. Williams *et al*[16] studied the relationship between physician utilisation and patient waiting time in an outpatient clinic using a staggered block scheduling system (eight patients arriving every half hour) *vs* the single block scheduling system (sixteen patients arriving simultaneously). The single block system emphasises the physician's idle time, whereas, the staggered block system emphasises the patient's waiting time, hence a substantial decrease in the patient waiting times (with no decrement in the utilisation of the physician) occurs with the staggered system.

Surgical (operating room) center scheduling has also been studied using simulation. Murphy and Sigal[17] examined surgical block scheduling, where a block of operating room time is reserved for an individual surgeon or a group of surgeons. Fitzpatrick *et al*[18] studied the use of first-come-first-serve, fixed, variable, and mixed block scheduling for hospital operating rooms. Fixed block scheduling is defined as scheduling the same block of time in the same time slot each day of the week. Similarly, variable block scheduling is scheduling under the influence of seasonal fluctuation in demand. Mixed block scheduling means using a fixed block for those procedures that are time consuming or require specialised set-ups, while using a variable block for all other procedures. They found that variable block scheduling is superior to all scheduling policies, in terms of facility utilisation, patient throughput, average patient waiting time, and patient queue length. Magerlein and Martin[19] reviewed the literature (prior to 1980) on using simulation for scheduling surgical centers.

Klassen and Rohleder[20] used simulation to study the best time to schedule patients with large patient service time differences and variances. They analysed several rules and arrived at the best result (which is to schedule such patients towards the end of the appointment session) that minimises the patient's waiting time and the physician's idle time. Additionally, they analysed the best position for unscheduled appointment slots for potentially urgent calls and found no conclusive scheduling rule. Likewise, Swisher *et al*[21] experimented on scheduling more patients with a larger service distribution in the morning session, rather than the afternoon, in an outpatient clinic. They found that staff overtime decreases sharply, but the amount of time the physician has for lunch also decreases. Another study concerning overtime was conducted by Steward and Standridge[22] in a simulation model of a veterinary practice. The veterinary domain is very similar to the larger human medical systems domain, since both involve the issues of flow and service rates, as well as resource utilisation, 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. This serves as an indicator of overhead cost and client satisfaction. The results from the study indicated that performance can be improved 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[23] attempted to use simulation to reduce variance in occupancy levels in a hospital inpatient facility, with the goal of increasing patient throughput and maximising average occupancies. Unfortunately, they were unsuccessful in achieving their stated objective, since the staff were accustomed to admitting patients on the date of the requests 90% of the time (and they refused to schedule over four weeks in advance). In another paper, Hancock and Walter[24] attempted to smooth the daily patient loads of 19 hospital departments by varying the admission days of urgent inpatient and outpatient loads. The variation in average load for each of the departments led them to conclude that no one single admission policy could provide a stable workload for all departments, since each department had its own unique patient arrival patterns and treatment requirements, including different inpatient and outpatient requirements.

Lim *et al*[25] applied two admission policies (quickcall and maximum queue lengths) to a simulation model of an inpatient orthopedics ward. 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 utilisation.

Using several different appointment schemes, Walter[26] describes several aspects of a queuing system in a radiology department. By segregating patients into inpatient and outpatient sessions with a similar examination time distribution, he found that substantial staff time savings were possible. He also found that the practice of giving multiple bookings for a given appointment time (that is, overbooking) yields a small increase in staff utilisation while substantially increasing the patient waiting time. Additionally, efficiency always improves when the proportion of patients with appointments increases, resulting in a smoothing of the arrival rate. Goitein[27] supported these 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 statistical fluctuations.

In conclusion, patient scheduling and admission rules along with patient appointment timing can both have a significant impact on physician utilisation and patient waiting times. In general, the studies using simulation discussed here suggest that rules and policies can be employed that will help to balance the tradeoff between physician utilisation 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.

Patient routing and flow schemes

One advantage of using discrete-event simulation over other mathematical modeling tools (such as linear programming and Markov chain analysis) when modeling a health care clinic is the capacity of simulation to model complex patient flows through health care clinics, and then to play 'what if' games by changing the patient flow rules and policies. Such flows are typical in emergency room settings, where patients arrive (without appointments), and require treatment over a large and varied set of ailments and conditions. These ailments can range from the benign (for example, mild sports injuries) to the fatal (heart attacks and gunshot wounds). Though the arrival of patients is highly unpredictable, the sequence by which patients can be treated (that is, routed) can be controlled by medical staff. By altering patient routing and flow, it may be possible to minimise patient waiting time and increase staff utilisation rates.

Garcia *et al*[28] analysed the effects of using a fast track lane to reduce waiting times of low priority patients in an emergency room. Emergency rooms are prioritised according to the level of patient sickness, hence low priority patients regularly wait for excessively long periods of time. A fast track lane is a lane dedicated to serving a particular level of patient (in this case, non-urgent patients). They found that a fast track lane that uses a minimal amount of resources could greatly reduce patient waiting times. In a simulation model of the emergency department at the University of Louisville Hospital, Kraitsik and Bossmeyer[29] suggested using a fast track lane as well as using a 'stat' lab for processing high volume tests to improve patient throughput. Kirtland *et al*[30] examined eleven alternatives to improve patient flow in an emergency department and selected three alternatives, that when combined, could save each patient an average of 38 minutes. The three selected alternatives were:

(i) using a fast track lane in minor care,
(ii) placing patients in the treatment area instead of sending them back to the waiting room,
(iii) the use of point-of-care lab testing.

McGuire[31] uses MedModel to determine how to reduce the length of stay for patients in an emergency service department in a SunHealth Alliance hospital. From the simulation study results, several alternatives were recommended, including adding an additional clerk during peak hours, adding a holding area for waiting patients, extending the hours of the fast track lane, and using physicians instead of residents in the fast track area. Blake and Carter[32] also analysed an emergency department at the Children's Hospital of Eastern Ontario. Based on their simulation results, a fast track lane for treating patients with minor injuries was implemented.

Ritondo and Freedman[33] showed 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*[34] compared 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 showed that patient waiting times could be reduced by up to 30% using quasi-parallel processing.

Scheduling and availability of resources

The majority of scheduling simulations for health care clinics are directed at patient scheduling (so as to distribute patient demand for the physician and the staff). A number of studies, however, have addressed the problem from the reverse side (that is, staff can be scheduled to meet patient demand, while the patient arrivals can be left unchanged). In fact, some clinics, such as walk-in clinics, are unable to change the arrival rate of patients and must schedule their staff accordingly. Furthermore, concurrent scheduling of staffing, as well as scheduling for the patients, could be used to better meet demand and allocate resources. Incorporating this idea, Alessandra *et al* 7[35] studied both staffing levels and patient arrival rates to ease bottlenecks and to improve patient throughput. Eight alternatives that involve varying the staffing pattern and the patient scheduling scheme were analysed. It was found that the best alternative was to keep the staffing and arrival rate the same, but to distribute the current morning appointment patients to the afternoon shift. Mukherjee[36] identified a staffing mix that reduces patient waiting time and increases patient throughput, while controlling resource costs in a pharmacy.

A number of simulation models of scheduling nursing staff in emergency departments have been developed, due to the high volume of emergency visits, as well as the urgency of the care required. Furthermore, hospitals are faced with pressures to maintain high quality health care while reducing or minimising costs. Draeger[37] simulated 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, they found an alternative that could reduce both the average patient time in system (by 23%) and the average patient waiting time (by 57%), without increasing costs. Similarly, Evans *et al*[38] reduced a patient's length of stay by finding the optimal number of nurses and technicians that should be on duty during four shift periods in an emergency room. Kumar and Kapur[39] examined ten nurse scheduling policy alternatives, selecting and implementing the policy yielding the highest nurse utilisation rate.

Lambo[40] applied a recursive linear programming and simulation methodology to examine staffing problems in a health care center in Nigeria. In this 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.

These studies suggest that when patient flow patterns cannot be controlled, staffing strategies can be employed to mitigate some of the unavoidable variability in the systems. This can result in improved patient throughput, while keeping staff utilisation rates at acceptable levels.

Allocation of resources

With the rise in the cost of providing quality health care, hospital and clinic administrators have approached cost containment by minimising resources for health care provisions while still striving to provide quality health care for patients. This predicament is becoming more prevalent in the health care community as indicated by the large body of literature that analyses the allocation of scarce health care resources. Simulation modeling is attractive since it can be used to estimate the operational characteristics of a system as well as to observe the consequences of changes in planning or policies prior to when decisions are actually implemented, hence reducing the financial risks. The allocation of resources can be divided into three general areas:

(i) bed sizing and planning,
(ii) room sizing and planning,
(iii) staff sizing and planning.

Each of these areas is discussed individually.

Bed sizing and planning

The demand for hospital or clinic beds can be decomposed into both routine (scheduled) and emergency (unscheduled) admissions. Both these types of admissions impact how many beds are needed to meet demand, while maintaining reasonable bed utilisation rates. In the literature, most bed planning simulation models attempt to overcome bed shortages or policies that lead to patient misplacement, bumping, or rejection. Hospitals are faced with the tradeoff between having available beds to service patient demand *vs* keeping bed occupancy (utilisation) rates high.

Butler *et al*[41] used 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 to various modifications in their bed allocation policy, including patient transfers, bed scheduling, and assignments. It was 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*[42] used a two-phase approach involving a quadratic integer programming model and a simulation model to evaluate bed configurations and to determine optimal bed allocations across a number of hospital service areas.

Lowery[43,44] and Lowery and Martin[45] studied the use of simulation in a hospital's critical care areas (for example, operating rooms, recovery units, intensive care units, and intermediate care units) and 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 demonstrated improvements in their methodologies over previous models. Dumas[46,47] also focuses on the interrelationships among 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 in the preferred unit. Vacancy basing rules utilise a ranked list of alternative misplacement possibilities, while home basing prohibits off-service misplacements, hence it is more restrictive with respect to patient placement. They showed that home basing policies resulted in better overall performance but less patient days, hence less revenue. Cohen *et al*[48] presented a bed planning model of a progressive patient care hospital, where patients are moved between units within a hospital as their condition changes. They demonstrated 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.

Looking at individual units within a hospital, Zilm *et al*[49] used simulation to model a surgical intensive care unit for various bed levels and future demand. They observed that most of the unit's volume consists of weekday cases (routine admissions) and consequently any attempt at a high overall occupancy level would not be possible without straining the system. Romanin-Jacur and Facchin[50] used simulation to study the facility dimensioning problem and the sizing of the assistance team in a pediatric semi-intensive care unit. They compared 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 turn of duty. Other bed sizing models include Hancock *et al*,[51] Wright,[52] and Harris.[53] Harris[53] compared the difference in the number of beds needed in a surgical center for three physicians under two operating timetable scenarios. Under the first (and current) scenario, each physician scheduled their patients independent of the other two physicians. In the second scenario, the physicians pooled their resources to schedule their patients and consequently reduced the number of beds required by over 20% (from 62 to 49).

Gabaeff and Lennon[54] used 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 simulation models, they highlighted deficiencies in a number of key areas, such as maximum bed utilisation exceeding current bed availability, which would cause displacement of minor care patients. Vassilacopoulos[55] developed a 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 showed that by using a waiting list and smoothing the patient demand, high occupancy rates could be achieved. Emergency department bed planning models were also simulated by Altinel and Ulas[56] at the Istanbul University School of Medicine; Freedman[57] at St. Joseph Hospital and Washington Adventist Hospital in Maryland, USA; Lennon[58] at the Stanford University Hospital; and Williams[59] at the University of Pennsylvania Hospital.

In conclusion, simulation provides a valuable 'what if' tool for hospital planners when deciding how many beds are needed to meet demand and maintain profitability. Moreover, simulation allows hospital administrators to experiment with different bed allocation rules to help optimally utilise hospital facilities and improve bed occupancy rates.

Room sizing and planning

The continuing trend towards the development of free-standing surgicenters, as well as the movement to deliver health care services away from inpatient facilities and more 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 patients. The use of computer simulation for the planning of future expansion, integration, and/or construction of new facilities and departments has greatly enhanced the hospital administration decision maker's ability to find the most cost effective and efficient solutions to remain competitive.

The number of and utilisation of operating rooms is often an important resource in maintaining hospital profitability and patient services. Currie *et al*[60] studied operating room utilisation, vertical transportation needs, radiology staffing, and emergency medical system operations at the West Virginia University Hospital. They arrived at an estimate for the number of operating rooms and recovery beds needed to handle a 20% increase in future demand. Kwak *et al*[61] used simulation to determine the capacity of a recovery room for an operating room expansion. Similarly, Kuzdrall *et al*[62] used a simulation model of an operating and recovery room facility to determine and assess the facility utilisation levels and facility needs under different scheduling policies. Olson and Dux[63] apply simulation modeling to study the decision to expand the Waukesha Memorial surgicenter from seven to eight operating rooms. This study revealed that an eighth operating room would only serve to meet the hospital's needs for one to two years, at a cost of \$500 000. However, an analysis of the cross-departmental and administrative needs reveal that an ambulatory surgery center that separates the inpatient and outpatient procedures would better serve the hospital's future health care delivery needs. Likewise, Amladi[64] used simulation to assist in the sizing and planning of a new outpatient surgical facility, by considering patient wait time (quality) and facility size (resource).

Meier *et al*[65] considered eleven scenarios in varying the number of examination rooms and demand shifts of both a hospital ambulatory center and a freestanding surgicenter. They found that existing room capacity was adequate to handle the demands for the next five years. Iskander and Carter[66] also found 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 suggested a threefold increase in the size of the waiting room.

Kletke and Dooley[67] examined the effects on service level and utilisation rates in a maternity ward to determine if the current number of labor rooms, delivery rooms, post-partum rooms, nursery, and nurses were able to meet future demands. Their simulation study recommends increasing the number of labor rooms and the number of post-partum rooms, while maintaining four full-time nurses.

Levy *et al*[68] analysed the operational characteristics of an outpatient service center at Anderson Memorial Hospital to determine whether to merge this service with an offsite outpatient diagnostic center. They collected data on the utilisation 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[69] simulated a proposal to combine an obstetrics clinic and a gynaecology clinic into one single facility in order to cut costs. The analysis using simulation found that this proposal would not be successful due to the shortage of examination rooms.

In conclusion, simulation provides a valuable tool in determining 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, simulation will also be useful in assessing how to best undertake this transition.

Staff sizing and planning

Quality health care delivery services require highly skilled medical professionals. This makes staff sizing and planning an important factor in designing health care delivery systems found throughout hospital units. Moreover, the tradeoff between insufficient staff to meet demand (hence unacceptable patient waiting times) and underutilisation of staff can have disastrous effects on the viability of a medical facility. Simulation has played an important role in addressing this tradeoff.

Several simulation studies have been conducted to determine the staff size or the number of physicians for emergency departments.[70–74] Badri and Hollingsworth[71] analysed the impact of different scenarios on scheduling, limited staffing, and changing the patient demand patterns in an emergency room of the Rashid Hospital in the United Arab Emirates. Several different scenarios were investigated:

(i) using a priority rule based on severity of ailment,
(ii) not serving a category of patient that does not belong in the emergency room,
(iii) eliminating one or more doctors on each shift,
(iv) a combination of (ii) and (iii).

The results from scenario (iv) were accepted and implemented. Klafehn and Owens[72] and Klafehn *et al*[73] addressed the linkage between patient flow and the number of staff available in an emergency department. They concluded that moving one nurse from the regular emergency area to a triage position reduces patient waiting lines and patient waiting times. Furthermore, the addition of a second orthopedic team in the emergency department increases patient flow, though utilisation 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[74] developed an M/M/n queuing model of the Campbelltown Hospital emergency facility. They used the model to estimate and develop patient arrival time distributions, patient waiting times, and patient service times. These parameters were then used in a simulation model to estimate the expected waiting time of the patients, the expected idle time of the doctors, and the optimal number of doctors. Gonzalez *et al*[75] evaluated eight alternative scenarios in an emergency department simulation, by varying the number of staff, the arrival rates, and the service times of diagnostic equipment (alterable by purchasing better equipment). They recommended that the arrival rate should not exceed twelve patients per hour. Moreover, they recommended that investments in human resources would be more effective than in newer (better) equipment. In contrast, Bodtker *et al*[76] and Godolphin *et al*[77] determined that a reduction in staff by at least one staff member could be achieved if better equipment were purchased.

O'Kane,[78] Klafehn,[79] and Coffin *et al*[80] analysed staff allocations to improve patient flow in a radiology laboratory. Klafehn and Connolly[81] modeled an outpatient hematology laboratory using Proof Animation from Wolverine Software. They compared a number of staffing configurations and found that if the staff is cross-trained (hence can be more fully utilised), then patient waiting times can be reduced. Vemuri[82] and Ishimoto *et al*[83] explored the operations of a pharmacy unit in a hospital. Using simulation, they found the optimal medical staff size and mix that reduces patient waiting times.

Hashimoto and Bell[84] conducted a time-motion study to collect data for a simulation model of an outpatient (general practice) clinic, they showed that increasing the number of physicians, and consequently the number of patients, without increasing the support staff, would significantly increase the length of stay for the patients. By limiting the number of physicians to four and increasing the number of dischargers to two, they were able to decrease the patient's average total time in the system by almost 25% (from 75.4 minutes to 57.1 minutes). Wilt and Goddin[85] evaluated patient waiting times to determine appropriate staffing levels in an outpatient clinic. McHugh[86] examined the staffing adequacy of various nurse-staffing levels and their effects on cost, understaffing, and overstaffing in a hospital. Her analysis showed that 55% of the maximum workload produces a good balance between the three measures. Swisher *et al*[21] discussed a simulation model of the Queston Physician Practice Network where individual family outpatient clinics are modeled and integrated into a network of clinics, with a central appointment scheduling center located in Virginia, USA. Performance measures such as patient throughput, patient waiting time, staff utilisation, and clinic overtime were analysed for various numbers of examination rooms and staff sizes. In certain cases, adding additional support personnel had negligible effects on the performance measures.

Stafford[87] and Aggarwal and Stafford[88] developed a multi-facility simulation model of a university health center, incorporating fourteen separate stations (for example, receptionist area, injections, dentist, gynaecology, 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 showed 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 this data, they investigated 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 showed 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 waiting times of the patients. However, these increases were offset by a significant decrease in the staff idle times and staff costs.

In conclusion, staffing levels and staff distributions have a significant impact on patient throughput and patient waiting times. Similar to facility sizing and planning, simulation can be used as an effective tool to study various staffing strategies for a wide variety of health care facilities and systems.

Discussions for future directions

There is a significant amount of literature on using simulation to study health care clinics. Publications based on such studies have steadily increased from eight in 1973–1977 to twenty-eight in 1993–1997 (and this number should continue to increase). Moreover, 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 simulation software packages (especially over the past five years). It also appears that a growing number of these studies attempt to combine optimisation techniques with discrete-event simulation. Future modelers are moving towards realising the advantages of simultaneously applying simulation and optimisation techniques. Despite the upward trend of health care simulation studies and the integration of discrete-event simulation and optimisation techniques, there is still a void in the literature focusing on complex integrated systems. This void may be due to the associated complexity issues and resource requirements. Moreover, no matter how complex the modeled system is or what techniques are applied, future modelers will continue to face difficulties implementing their results. However, recent advances in simulation software may alleviate some of these difficulties. The following subsections are devoted to a discussion of these topics and issues.

Complex integrated multi-facility systems

A limited number of simulation models have been developed that analyse complex multi-facility healthcare delivery systems. Most simulation models, such as the ones described previously, report on individual units within multi-facility clinics or hospitals. Using a macroscopic analysis of multi-facility systems, simulation can be used to estimate patient demand load (directly related to arrival rates), utilisation 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. Simulation models that depict the interaction of major service departments and support services in a hospital, and the information that can be gained from analysing 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 organisations (HMO), multi-hospital, or multi-clinic organisations. This presents a challenging application for 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*,[11] Aggarwal and Stafford,[88] Hancock and Walters,[24] Swisher *et al*,[21] and Lowery and Martin.[45]

One 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 analysing 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 organisations. 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:

(i) the level of complexity and resulting data requirements of the simulation model,
(ii) the resource requirements, including time and cost.

A widely recognised guideline in 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*[89] who stressed 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. Additionally, Lowery[8] suggests using simple analytical models if they can provide the level of detail required. However, when analysing integrated systems, most studies require a level of detail that will far exceed 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). A methodology that aids in determining the level of detail and identifying system boundaries is suggested by Lehaney and Paul[90,91] and Lehaney and Hlupic.[92] They suggest using soft system methodology (SSM) to aid in determining the level of detail, identifying system boundaries, and ascertaining system activities, particularly in complex models. 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 environment is rapidly changing and if the process of developing and searching for a solution requires a large investment in time, the system may be outdated before the simulation becomes useful. Consequently, an adequate amount of resources must be dedicated to the project to insure 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 simulation software package that would ease the development of complex models, and the cost of skilled consultants or in-house engineers may all be prohibitively high.

Combining simulation and optimisation techniques

Unlike analytical methods, simulation is not an optimisation tool. Simulation can only provide an analyst with estimates of performance measures for various system alternatives. Moreover, simulation models typically have several output performance measures upon which to optimise, hence creating a multi-criteria objective function environment.

There are several advantages and disadvantages of using either simulation methodology or optimisation techniques to model complex systems. Davies and Davies[93] and Stafford[94] compared 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 found that simulation is particularly suitable for modeling health care clinics due to the complexity of such systems. This is because many optimisation techniques, such as linear programming, have a limited capacity for characterising the complexities of medical systems. An optimisation technique may require too many unrealistic assumptions about the process, hence rendering the solution invalid. For example, optimisation models cannot be used to study the details of the day to day functions of a medical clinic, such as appointment scheduling, service routing, and service priorities, which can be easily handled by simulation. On the other hand, many optimisation 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, simulation requires a large amount of effort in time, cost, and data needs. For all of these reasons, operational researchers have attempted to combine simulation with deterministic operational research techniques, such as linear programming, to capitalise on the advantages of using both techniques simultaneously.

Several health care analysts have successfully combined these techniques to find the best staffing allocations and facility sizes.[42,95–98] A common technique when applying an optimisation methodology to simulation models of health care clinics is a recursive method employed by Carlson *et al*,[95] Kropp *et al*,[96] and Kropp and Hershey.[97] First, an optimisation technique is used to analyse and reduce the number of alternatives of the system at an aggregate level (the total system level). These results are then used in a more complex and detailed simulation model of the same system, that identifies additional information and acceptability of the results. Finally, these additional constraints are passed back into the optimisation model and this process is repeated. Similarly, Butler *et al*[42,98] employed a two phase approach by first using quadratic integer programming for facility layout and capacity allocation questions, and then a simulation model to capture the complexities of alternative scheduling and bed assignment problems.

All of the above studies use a variety of optimisation techniques to arrive at parameters for the simulation model. Generally, recursive simulation optimisation techniques can be very difficult, and therefore, costly to implement in the health care sector. However, in recent years, a number of simulation software packages have appeared that provide an optimisation add-on to the software.[99] Instead of an exhaustive, time-consuming, and indiscriminate search for an optimal alternative, 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.[100] Other optimisation simulation software includes ProModel's SimRunner Optimisation[101] and AutoStat for AutoMod.[102]

Advances in simulation software

In recent years, simulation software has undergone a series of technological leaps. First, the introduction of visually oriented graphical outputs greatly aids in the verification and validation of models and results,[103,104] though this does not necessarily guarantee model correctness.[105] Moreover, animation in simulation is primarily used to present (to decision-makers) the actual operation of the model and system and, in essence, to sell the insights of the system. Secondly, the wide use of the object-oriented paradigm (OOP) in simulation software design enables analysts to model a system without writing a single line of code.[106] Numerous companies are developing general-purpose software packages incorporating the latest technologies.[107] Some such packages are specifically aimed at the health care industry, such as MedModel[108,109] and ARENA with a health care template.[110]

Jones and Hirst[111] presented one of the early articles on using visual simulation, using the simulation software package See-Why. The visualisation 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[112] used a generic simulation package called CLINSIM to illustrate how clinic appointments and operating policies can influence patient waiting time. Evans *et al*[38] used ARENA to model an emergency department using thirteen patient categories. They reduced the patient's length of stay using alternative scheduling rules for the number of nurses, technicians, and doctors on duty during each particular hour of the simulation run. Besides these studies, several other visual simulation modeling projects of interest have been conducted.[31,33]

The number of health care organisations and government agencies using these advanced simulation packages has grown, with much of their work and the results of their efforts not available in the literature. Considering the number of easy to use 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 fact that since simulation models have become easier to develop with these new simulation software packages, the type of users have changed. Although the number of operational research analysts and management engineers conducting simulation projects are unknown, numerous non-technical, and therefore non-publishing, users have emerged. It is no longer necessary to have an advanced degree in operational research or simulation to use simulation software packages because it is virtually a drag-and-drop operation. However, this development does not diminish the importance of the contributions from operational research professionals to the health care field. They will still be required to provide expertise when conducting or managing critical or large-scale simulation projects.

Implementation issues

Simulation modeling of health care clinics has been extensively used to assist decision-makers as well as to improve efficiencies. For simulation to reach its greatest potential as the key tool for analysing health care clinics, simulation results must be implemented. Unfortunately, in a survey of two hundred papers of simulation in health care, Wilson[113] found only sixteen projects reported successful implementations. A number of recommendations were given to increase the chances of success in implementation. These recommendations include:

(i) the system studied is in need of a decision,
(ii) the project must be completed before a deadline,
(iii) data must be available,
(iv) the organizer or the decision maker must participate in the project.

Lowery[8,114] addresses some additional barriers, as well as solutions to help overcome the resistance to implementation. Some of the suggestions include animating the simulation to 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. Additionally, they suggest management engineers must simplify the simulation process and improve their sales skills. Marsh[115] listed three key elements necessary for the successful implementations of simulation results:

(i) total commitment and support from the user,
(ii) credibility of the model,
(iii) the analyst must work with the real operations on hand instead of any esoteric studies.

Despite the lack of implementation observed in the literature, other benefits can still be gained from conducting a simulation study. The procedure and methodology of applying 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 offered by the system. Rakich *et al*[116] studied the effects of simulation in management development. They concluded that simulation not only develops a manager's decision-making skills, but also forces him/her to recognise the implications of system changes. Also, in agreement with Wilson, in the cases where managers developed their own simulation models, implementation occurred very easily. Finally, Lowery[8] realises that there are benefits, such as identifying unexpected problems unrelated to the original problem, that arise even if implementation fails.

Conclusions

This paper presents a survey of the literature (focusing primarily on the past twenty years) on applying discrete-event simulation to understand the operation of health care facilities. This survey shows that a large amount of research has been conducted in the area of patient flow as well as resource allocation. The multiple performance measures associated with health care systems makes simulation particularly well-suited to tackle problems in this domain. The numerous simulation studies reported in the literature have the common theme that they each attempt to understand the relationship that may exist between various inputs into a health care system (for example, patient scheduling and admission rules, patient routing and flow schemes, facility and staff resources) and various output performance measures from the system (for example, patient throughput, patient waiting times, physician utilisation, staff and facility utilisation). The breadth and scope of units within hospitals and clinics makes it impossible to undertake one single comprehensive study that addresses all these issues simultaneously.

These observations, together with the void 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, a number of observations were made about the continuing trends in simulation software, such as the development of optimisation add-ons, increased visualisation, and the shift to an object-oriented paradigm. These powerful features will have the most impact when educating decision-makers on what changes need to be made and lessening resistance to implementation. The outlook for simulation in health care looks promising. The further development of more powerful high speed processing, distributed simulations,[117] and object-oriented simulation, will facilitate the creation of complex, but tractable, models of large integrated systems, with the results implemented more easily and frequently.

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