Discrete Event Simulation of Emergency Department Activity: A Platform for System-level Operations Research

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Abstract

Objectives: This article explores the potential of discrete event simulation (DES) methods to advance system-level investigation of emergency department (ED) operations. To this end, the authors describe the development and operation of Emergency Department SIMulation (EDSIM), a new platform for computer simulation of ED activity at a Level 1 trauma center. The authors also demonstrate one potential application of EDSIM by using simulated ED activity to compare two patient triage methods. **Methods:** The *Extend* DES modeling package was used to develop a model of ED activity for a five-day period in July 2003. Model input includes staffing levels, facility characteristics, and patient data drawn from electronic patient tracking databases, billing records, and a detailed review of 674 ED charts. The accuracy of model output was tested by comparing predicted and known patient service times. The EDSIM model was then used to compare the fast-track triage approach with an alternative acuity ratio triage (ART) approach whereby patients were assigned to staff on an acuity ratio basis. **Results:** The EDSIM model predicts average patient service times within 10% of actual values. The accuracy of individual patient paths, however, was variable. In the authors' model, 28% of individual patient treatment times had an absolute error of less than one hour, and 59% less than three hours. A preliminary comparison of two triage methods showed that the ART approach reduced imaging bottlenecks and average treatment times for high-acuity patients, but resulted in an overall increase in average service time for low-acuity patients. **Conclusions:** The EDSIM model provides a flexible platform for studying ED operations as they relate to average treatment times for ED patients, but the model will require further refinement to predict individual patient times. A comparative study of triage methods suggests that ART provides a mix of benefits and drawbacks, but further investigation will be required to substantiate these preliminary findings. **Key words:** computer simulation; medical informatics; emergency medicine; resource allocation. ACADEMIC EMERGENCY MEDICINE 2004; 11:1177–1185.

Nationwide increases in emergency department (ED) patient census and acuity,[1] ongoing ED closures,[2] and crisis-level overcrowding problems[3–8] have led to increased interest in analytical methods that allow ED activity to be studied at a system level.[9,10] In an important 2003 study, Asplin et al.[11] described the conceptual relevance of an input–throughput–output approach in the analysis of factors contributing to ED overcrowding.[11] This engineering framework provides a basis for quantitative analysis of ED patient flow, wait times, treatment times, and the factors that influence these outcomes. Potential applications of this approach range from investigating the causes and consequences of overcrowding to developing methods for increasing ED efficiency and evaluating disaster response scenarios.

One method for conducting quantitative input–throughput–output analyses is through detailed computer simulation of ED patient flow. A branch of computer simulation science called discrete event simulation (DES) has been developed to allow modeling of discontinuous systems by defining activity as a network of interdependent discrete events.[12,13] DES approaches have been used to study and optimize a vast array of complex systems ranging from the behavior of Internet server hubs to priority mail tracking schemes and airport security systems, and numerous studies are presented at the Institute of Electrical and Electronics Engineers (IEEE) Annual Winter Simulation Conference.[14] DES models do not attempt to solve mathematical representations of a system (as with queuing theory) or generate empirical fits and extrapolations of known system behavior. DES models enact actual events using data elements that represent—in the case of health care applications—patients, staff, laboratory and imaging

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studies, and associated resources. In an ED, all of the events that make up a patient's stay—wait time, procedures, interaction with staff, imaging studies—are played out using the same priority-based thinking that drives actual ED operations. Readers interested in learning more about DES methods can download a free DES demo at www.imaginethatinc.com (makers of the simulation software used for the EDSIM model). This demo includes simple models and allows users to build their own models.

Efforts to develop computer simulations of ED operations have been advancing since the late 1980s when Saunders et al. simulated a generalized ED.[15] Since that time, DES models and other simulation techniques have been used to study a wide range of factors such as the effect of staffing levels,[16–19] the consequences of complete and partial ED closures,[20] and variables influencing patient throughput.[21–24] For example, Ohboshi et al.[25] studied emergency medical services (EMS) response to the Hanshin-Awaji earthquake of 1995. Huddy et al.[26] have described the broad potential for ED simulation. In some studies, researchers have generated models that were able to make accurate predictions of quantities such as waiting room times and patient care times.[17] In addition, numerous studies have identified opportunities for significant improvement in ED operations. For example, McGuire[22] studied a wide array of potential alternatives for reducing patient wait time and identified a range of shift modifications that resulted in a 50-minute reduction in average length of stay. DES and related computer-simulation techniques have also been applied to other aspects of health care, and introductory articles[27,28] and advanced studies[29–40] are available.

In this article, we describe the development and operation of Emergency Department SIMulation (EDSIM), a newly developed DES model of ED activity in an academic Level 1 trauma center. Several factors set the EDSIM model apart from previous modeling efforts. The EDSIM model is the first to combine a DES modeling platform with a data-intensive "patient path step" approach for simulating ED activity. The EDSIM project also represents the first patient-chart–based computer simulation of an academic ED. Also unique is EDSIM's combination of continually updated job queue prioritization and midtask preemption capabilities that together allow the model to capture the chaotic nature of ED staff activity. Recent advances in computer simulation technology and in ED electronic patient tracking systems have made the EDSIM model possible. Therefore, this project highlights the key role information technology has in the study and optimization of ED activity.

METHODS

Development and Structure of the EDSIM Model. EDSIM was developed through a cooperative effort involving the University of California, Davis, Medical Center (UCDMC) Department of Emergency Medicine and the UCDMC billing department over a two-and-a-half-year period. Patient chart review and associated data entry and patient path development constituted one year of this effort. The Extend Suite v.5 modeling platform developed by Imagine-That, Inc. (www.imaginethatinc.com), was used to develop the core model and associated data entry and data processing tools. Extend provides a DES platform with an integrated database and an object-oriented programming environment that allows a model to be built by assembling modules that represent packages of prewritten code. The modules are connected by conduits that carry data elements representing patients, staff, orders, laboratory results, images, etc. Modules can be arranged hierarchically with top-level windows defining the overall model structure and sublevel windows containing additional modules that drive more detailed analyses.

EDSIM's core engine runs a patient-care–directed algorithm. Each patient seen in the modeled ED has a set of instructions that define a series of individual activities that must be completed in correct order before that patient leaves the ED. These instructions define each patient's "path" through the ED. The patients modeled by EDSIM all have a defined but variable set of clinical needs. Elements of patient care can include imaging studies, laboratory studies, history and physical examination, nursing activity, consultations, and bedside procedures such as suturing, casting, and intubation. Running on an Intel (Santa Clara, CA) 3.1 GHz Xeon dual-processor workstation with 1.5 Gb of random-access memory, the EDSIM model runs approximately 300 times faster than real time (i.e., a day of ED activity can be simulated in less than 5 minutes). EDSIM also functions, albeit with longer run times, on Pentium-IV class single processor systems. Since the EDSIM model has 574 windows containing a total of 12,714 computational modules, the model cannot be shown here in its entirety. Additional images of the model's primary computational windows have been posted on the Internet http://www.nextinvention.com/EDSIM/EDSIM.html. This project was approved by the UCDMC Institutional Human Subjects Review Board.

Patient Population and Staff Activity. Modeled patient activity was based on actual patient experience in the UCDMC, which is a Level 1 academic trauma center with an annual ED census of approximately 60,000. The patient population in the model was drawn from the 682 patients cared for in the UCDMC ED from July 2 through July 6, 2003. All patients seen during this five-day period were eligible to be included in the study. As shown in Table 1, 573 patients were included in the modeled patient

TABLE 1. Actual and Modeled Patient Populations Stratified by ED Treatment Area

	ED Area-stratified Patient Population				
	Area 1	Area 2	Area 3	Area 4	Total
Number (%) treated in ED by area for 6-mo period beginning July 1, 2003	9,928 (34.7%)	6,606 (23.1%)	7,198 (25.2%)	4,875 (17.0%)	28,607
Number (%) treated in ED by area July 2 through July 6, 2003	213 (31.2%)	158 (23.2%)	175 (25.7%)	136 (19.9%)	682
Number captured in model cohort and area count and % of total	156 (27.2%)	137 (23.9%)	146 (25.5%)	134 (23.4%)	573
Percent of actual patient cohort captured in modeled cohort	73.2%	86.7%	83.4%	98.5%	84.0%

Number captured includes all patients treated in ED for whom a complete data set was available.

population. Random lapses in data acquisition and a periodic inability to unambiguously match a patient's database records from two or more data sources account for the 109 patients not included in the modeled population.

For the tests of model accuracy, actual patient arrival times for the modeled population were used. For the triage analysis, patient data were used to create four patient pools corresponding to the four UCDMC ED patient-treatment areas. To model a full seven-day period of ED activity, patients were pulled from within each patient pool at random. This was done while keeping the proportion of patients pulled from each pool equal to the actual proportion of patients seen in each area of the ED. For the patient pool method, patient arrival times during the five-day study period were used to create an exponential distribution of patient interarrival time. Interarrival time is the time between patient arrivals. The exponential distribution is the standard distribution to use for fitting interarrival times: Probability of interarrival time $P(t) = \alpha e^{-\alpha t}$ where the constant α is adjusted to provide the best fit to the actual distribution of interarrival times (which were shown to follow an exponential distribution). By sampling patients at random from within each patient pool and using an exponential distribution function to generate interarrival times on a probabilistic basis, a wide variety of arrival sequences and arrival times were simulated while maintaining a representative population.

When patients in the model arrived at the ED, they were assigned a triage priority and the ED area where they were to be seen (actual assigned priorities and areas were model inputs). The time at which a patient was called to a bed was determined by bed availability as dictated by the simulated ED activity. Once a patient was called to an ED bed, step-by-step instructions defining that patient's treatment path were delivered to the appropriate prioritized job queues where they were prioritized against jobs for the other patients in the ED. These instructions were derived from billing data and individual chart review for actual patients seen in the ED. The four areas of the UCDMC ED were modeled as quasi-independent units that shared laboratory and imaging facilities. Individual staff types were modeled and assigned appropriate responsibilities. When acute needs for staff arose, the model allowed staff to move temporarily between ED areas. In anticipation of ambulance arrivals, radio call-ins by EMS personnel were used to activate trauma and resuscitation codes before patient arrival. Both procedure-specific and routine nursing activity were simulated. The model also incorporated estimated admission delays for both surgical and nonsurgical patients.

All staff activities were prioritized according to patient acuity. EDSIM sends all patient care activities to prioritized ''job queues''—one queue for each staff member—where tasks are continually sorted by priority. In addition to job queue priority sorting, EDSIM also allows emergency situations, such as trauma and resuscitation codes, to preempt lower-priority activities, so that the needed staff member will immediately drop his or her current activity in midstream to handle the emergent situation. The dropped activity is returned to the prioritized job queue. The continual reshuffling of prioritized tasks and the preemption of activities by emergent situations together cause individual patient care to be continually interrupted by the needs of other patients and thereby allow the model to capture the chaotic and ever-changing nature of ED staff activity.

Although the model allows the priority of each individual step of a patient's treatment path to be specified, in practice it was difficult to determine the *relative* priorities of individual treatment steps with any degree of accuracy. To model the priorities of patients in the ED, we assigned the initial evaluation of all trauma and resuscitation patients the highest priority. The staff member required to respond to these codes would preempt (i.e., immediately stop) his or her current activity. Jobs for patients assigned the top two priority levels at triage were given the next highest priority. Patients assigned lower priorities at triage were given lowest priority in the modeled ED.

Data Sources and Model Inputs. Computer simulation of ED activity by the patient treatment path method is a data-intensive process. The staffing levels

TABLE 2. Modeled UCDMC ED Facility Characteristics

ED characteristic	Model inputs			
ED patient treatment areas	Area 1	Area 2	Area 3	Area 4
Patient population	High-acuity	Pediatric	Mid-acuity	Low-acuity fast track bay for urgent care
Beds (not including hall space)	12 general beds and 2 trauma bays	5 general beds and 2 trauma bays	13	6 general and 2 procedure rooms
Average staffing:				
Nurses	4	2	2	1
Resident physicians	2	2	1	1
Attending physicians	1	1	1	1
Imaging resources	Redundancy		Imaging time	Image read time
Portable radiography	1 unit		15	5
Fixed radiography	2 units		20	5
MRI	1 units		60	10
CT	2 units		30	15
Ultrasound	2 main units, plus portables		30	5
Cardiac stress test	2 bays		60	30
Laboratory resources	Laboratory times are based on lab technician estimates and range from 20-45 min. Laboratory analysis modeled as two-stage batch processing (spin down followed by analysis) for blood and urine samples. Any number of labs that arrive before batch processing commences are allowed to process simultaneously within defined batch period. No new labs started while batch was processing.			

and available resources used in the model are summarized in Table 2. Patient arrival times, call times, assigned ED treatment areas, departure times, and immediate dispositions after triage were obtained from the ED's electronic triage and Quickview (UCDMC) patient tracking databases. Patient billing data were used to determine which procedures, laboratory analyses, and imaging and other studies were actually billed to each patient seen in the ED. These billing data were then used in conjunction with a patient-by-patient chart review to reconstruct the series of staff activities and resource requirements associated with each patient's course of care in the ED. Modeled staffing activities and associated staff estimates of average procedure times are listed in Table 3.

TABLE 3. Modeled Activities and Associated Time Estimates

Staff Activity	Minutes
Hall triage	5
Waiting room triage	15
Assessment (resident)	5
Consult	30
Initial H&P	15
Procedure: resident MD	10
Procedure: RN	3
Routine nursing: check vitals	5
Routine nursing: check patient	3
Level 1 trauma / resuscitation	20
Level 2 trauma / resuscitation	20
Independent activity: attending	5
Independent activity: resident	5
Independent activity: nurse	5
Patient visit: resident	5
Patient visit: attending	5
Patient visit: resident & attending	10
Parting instructions	5

Despite the detailed, patient-by-patient chart review, several elements of patient care, such as time for physician assessment of new information, were not well captured in charts or billing data. In an effort to account for these types of activities, known elements of patients' treatment paths were added to the basic patient care template shown in Table 4. While this template will undoubtedly differ substantially from the actual course of care in some instances, it reflects the most common steps in the care of a patient with an undifferentiated complaint.

Two primary indicators were used to compare modeled and actual ED activities during the five-day study period. The first was patient *treatment* time. This was defined as the total time a patient spends in the ED from the point that he or she is assigned a bed in the ED to the point when he or she is admitted, is discharged, or otherwise departs. The second indicator was overall patient *service* time. Service time is the sum of treatment time and wait time before being assigned an ED bed.

EDSIM by Example: A Comparative Analysis of Two Triage Methods. To provide an example application of DES to ED operations research, we used the EDSIM model introduced in the preceding sections to conduct a preliminary evaluation of the patient throughput and resource use implications of a novel triage concept called acuity ratio triage (ART). In our analysis, ART was compared with the more traditional fast-track (FT) approach.

TABLE 4. Generic Patient Care Template

Activity Sequence Template	Activities Represented
Procedure: RN	Patient directed to bed. Initial activities such as IV, pulse ox.
Initial H&P	Resident meets with patient.
Assessment (resident)	Resident assesses findings.
Patient visit: resident & attending	Resident and attending see patient together and discuss initial plan.
Initial order # 1	All initial orders. Initial labs are followed by initial images.
Initial order # 2, etc	
Initial order # last	
Assessment (resident & attending)	After results of initial lab and imaging studies are returned, resident and attending develop a plan for subsequent care.
Patient Visit: resident	Resident discusses plan of care with patient.
Subsequent order # 1	Subsequent orders as listed chronologically in the chart. May include additional labs and images, consults, and procedures in the ED.
Subsequent order # 2, etc	
Subsequent order # last	
Patient visit: attending	Attending sees patient before departure or admission.
Parting instructions	Resident gives final instructions to patient.
Departure	Patient departs or is admitted.

For trauma or resuscitation patients, the first four steps of the template are replaced by a general trauma patient assessment activity.

The issue of how to manage low-acuity (LA) patients who could wait indefinitely if triaged on a purely priority basis is a common concern in a busy ED. Many EDs use an FT triage approach that allows LA patients to be cared for in an FT bay set aside for lower-acuity care. The alternate approach that we were investigating involves triaging patients on an acuity ratio basis (without a separate FT bay). This type of triage relies on assigning each care provider a set ratio of high-acuity (HA) to LA patients. Each time a patient is discharged (or admitted), the information is sent to triage to allow a new patient of the same triage priority to be assigned to the staff member who discharged the last patient. In this way, each physician and nurse works with a nearly constant patient acuity ratio.

In the model, data from the 422 patients actually seen in the HA and FT areas of the ED were used for analysis of the ART–FT comparison. The LA patient group was defined as the 248 patients from the HA and FT areas that were assigned the lowest two tiers of triage priority. The HA patient group was defined as the remaining 174 patients who were triaged as mid or top triage priority. Some mixing of LA and HA patients in the HA area occurred in the existing FT system, but staff activities in the HA and FT areas were completely separate (e.g., a physician with downtime in FT did not go to the HA area to attend patients). The two areas did, however, share imaging and laboratory facilities.

To model the ART approach, staff and beds from the HA and FT areas were combined into a single mixed-acuity treatment area that managed all of the 422 patients (59% HA and 41% LA). This modeled treatment area had a total of 20 beds (all 12 beds from the HA area and all eight beds from FT) and the combined staffing of these two areas. LA and HA patients were assigned to staff according to a set acuity ratio that did not have to equal the ratio of HA:LA patients in the presenting population. The desired acuity ratio was set by initially assigning LA and HA patients to each physician and nurse until the appropriate ratios were reached. These ratios were then maintained by assigning patients to staff on the basis of patient departure.

We used the stratified patient pool sampling method described in the previous section to evaluate each triage method for a period of one week. During this time, 800 patients (all drawn from the 573-member representative patient pool) were incorporated into the simulation. With the exception of triage methodology, all simulation parameters—patient population (both times and types of patient presentation), staff numbers, available resources, and total ED bed count—were identical in the two simulation scenarios.

RESULTS

Tests of Model Accuracy. Using patient data from the five-day study period and comparing model output with known patient treatment and service times, the EDSIM model overestimates average treatment time by 8% and underestimates average service time by 9%. Table 5 shows the corresponding results for average treatment and service times stratified by ED area. For individual patient times, EDSIM was less accurate: 28% of modeled patient treatment times have an error of less than one hour, whereas 59% of known patient treatment times have an error of less than three hours. For individual patient service times, 18% of the modeled had an error of less than one hour, and 46% of the known had an error of less than three hours. EDSIM predicts average patient times with better accuracy than individual patient times because

TABLE 5. Actual and Modeled Average Patient Times

	Average Treatment Times			Average Service Times		
	Actual	Model	% Error	Actual	Model	% Error
Area 1	412	402	−2%	513	420	−18%
Area 2	177	149	−16%	279	172	−38%
Area 3	382	307	−19%	515	322	−38%
Area 4	149	387	159%	289	557	93%
Overall	294	318	8%	409	372	−9%

there is no strong bias toward over- or underestimation—some patient times are overestimated; others are underestimated. Figure 1 shows how simulated treatment times compare on a patient-by-patient basis with actual treatment times during the corresponding study period for the 573 patients in the modeled cohort.

Triage Analysis. To directly determine the effect of varying the acuity mix that each care provider manages, the ART and FT triage systems were compared at an equal HA:LA ratio. In the FT system, HA:LA ratio corresponds to the ratio of FT to HA beds. In the ART system, HA:LA ratio refers to the ratio of HA to LA patients attended by each staff member. In each case, the total bed and staff numbers are equal. Average treatment and service times for HA and LA patients with each triage method are compared using an HA:LA ratio of 12:8. This ratio was chosen because it corresponds to the *actual* HA to FT bed ratio used during the study period. Relative to the existing FT configuration, the ART approach reduces average wait times by 76% and average treatment times by 4% for HA patients. However, this approach also results in an overall increase in average service time for LA patients. This increase is the result of a combined 25% reduction in average LA treatment time and a 329% increase in average LA wait time.

To further characterize the operational consequences of each triage method, associated changes in staff activity and resource-use bottlenecks were calculated. In the EDSIM model, the ART method reduces imaging bottlenecks relative to FT triage (maximum wait time reduced by 52% for computed tomography [CT] scan and 16% for radiography).

Overall, this comparison of ART and FT triage methods shows a variety of associated differences in ED operations. ART reduced average treatment times for all patients in the mixed-activity treatment area and reduced certain imaging bottlenecks (i.e., CT scan and radiography), but resulted in an overall increased service time for LA patients. These results are preliminary and intended for the purpose of demonstrating an application of DES to operations research in emergency medicine. It is too early to draw definitive conclusions about the relative benefits of these two triage approaches.

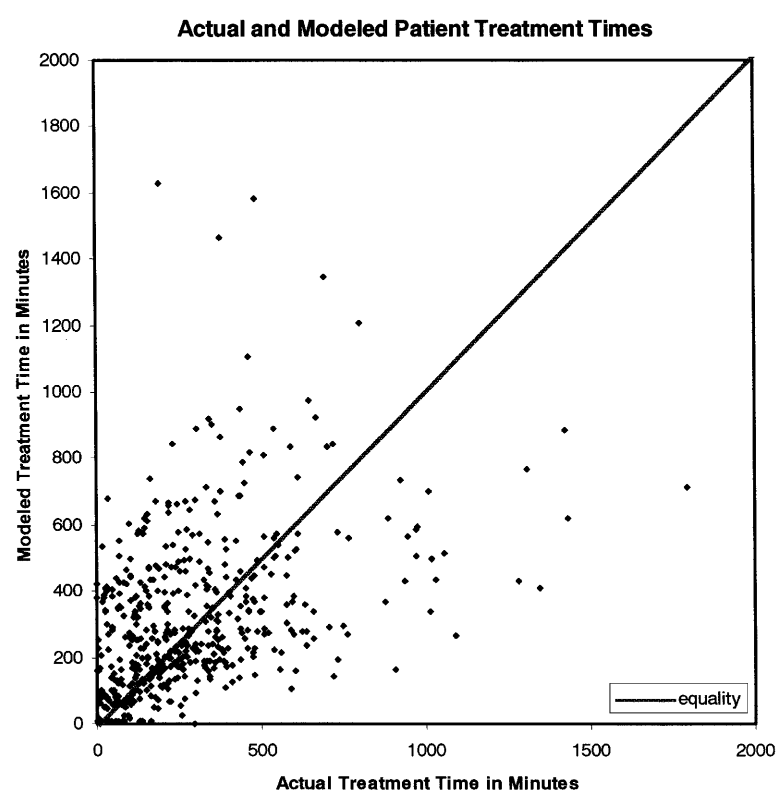

Figure 1. Modeled versus actual patient treatment times.

DISCUSSION

The time-intensive patient-by-patient chart review used to generate individual patient treatment data for the 573 patients included in the EDSIM cohort is both a strength and a weakness of this modeling approach. The modeled patient evaluation and treatment steps are not necessarily the textbook steps for the presenting condition, but rather the actual sequence of activities as reported on individual patient charts—a far more realistic yardstick. In addition, chart review allowed us to better account for the type and degree of staff involvement with each patient. The disadvantage is the time-consuming nature of the chart-review process that limits overall cohort size and the number of cohorts that can be constructed in a reasonable period of time.

One consequence of working with a single patient cohort of limited size is the potential bias that arises: we have not explicitly shown that the average procedure times used for the current patient cohort would, if used for a different cohort, generate the same (or better) degree of accuracy in predicting treatment times. However, the resulting bias is small because the procedure times used in the tests of model accuracy are constant over the five-day study period during which the number and type of patients in the ED were continually changing.

As with any study, simulation results are generalizable to the extent that the modeled conditions match the circumstances to which the study results are applied. The default patient care template, prioritization methods, patient presentations, and procedure times used in the EDSIM model are typical of Level 1 academic trauma centers of similar patient census and acuity. However, the EDSIM model itself is more broadly applicable. Because the architecture is not built around a single patient cohort, an unlimited mix of patient presentations, acuity levels, and arrival rates can be studied on the EDSIM platform. Similarly, because all department-specific resources (staffing levels, bed numbers, imaging and laboratory resources) are user inputs, the model can quickly be adapted to simulate ED environments ranging from an academic trauma center to a rural urgent care setting.

LIMITATIONS

Several factors contribute to the observed differences between actual and modeled patient times. In our patient population, 16% of the actual patient population was not captured in the modeled patient cohort. This is the result of various omissions or inconsistencies in the many data sources used to assemble patient care. These data gaps are random and do not bias the modeled patient cohort.

We found that staffing levels varied widely, not only during the course of the day owing to routine shift changes, but also in a far less regular pattern as the result of nursing shortages and other staffing issues. The constant variations in staffing levels caused by staffing issues were not tracked and recorded for research purposes during the time period we studied. Therefore, we were unable to model changes in staffing level for the tests of model accuracy. This limitation will bias the accuracy tests toward a less-accurate match. Changes in staffing level were intentionally omitted from the triage analysis because they would have led to temporal variation in staff-to-patient ratios and made the results of this preliminary study more difficult to interpret.

Because the tests of model accuracy were performed using *actual* interarrival times for patients during the study period, they do account for diurnal variation in patient arrival rate. The triage analysis used an exponential distribution to model the interarrival times for patients drawn from the stratified patient pool. This distribution function did not reflect diurnal, weekly, or seasonal variations in patient interarrival time.

Other limitations of this study involve the accuracy of individual patient treatment paths. Although a substantial amount of data about patient care can be assembled through a combined review of patient charts and billing records, some staff activities are not recorded in charts or billing data and are thus untraceable. In addition, the relative priorities of individual patient care steps can be dynamic and our prioritization based on triage categories is a necessary generalization. While we acknowledge that this system of prioritization is an imperfect descriptor of individual treatment path steps, it does correspond to the general triage scheme that is used in many EDs.

APPLICATIONS OF DES TO EMERGENCY MEDICINE OPERATIONS RESEARCH

All simulation studies reflect our sometimes limited understanding of what we are attempting to simulate. Simulations generate rapid reconstructions of complex events according to rules that we as investigators define. To the extent that events are governed by rules we do not appreciate, the unknown effects of these rules will be lost to the simulation. Therefore, simulation studies are best interpreted as "pretrials" that provide relatively inexpensive information that allows us to test our own understanding of factors influencing complex situations and to better determine which strategies for optimizing ED operations are worth further investigation through clinical trial.

Although DES models of ED activity have a broad range of potential applications, one of the most promising areas is the study of ED overcrowding. Several researchers have begun to use quantitative methods to look for associations between specific contributors and measurable consequences of overcrowding.[9,10,41–45]

One specific example is the recent effort by several researchers to develop broadly applicable, quantitative indicators of crowding level.[46–48] In another example, Chan et al.[49] used regression methods to study variables that affect patient throughput at the Albany Medical Center in New York. Davis et al.[50] looked for factors influencing ED length of stay for surgical critical care patients, and Huang et al.[51] used logistic regression analysis to identify factors contributing to frequent use of a Taiwanese medical center. These analyses help identify specific variables with which overcrowding is statistically associated, but they do not define the causal relation. An essential capability afforded by DES simulation is the actual reconstruction of the phenomena that lead to overcrowding. This allows a more detailed understanding of the relationship between the observed conditions and related outcomes.

CONCLUSIONS

Recent gains in DES modeling technology and ongoing advances in ED data tracking allow for detailed, patient-chart–driven computer simulation of ED activity. The EDSIM model demonstrates the growing potential of DES approaches to advance ED operations research. Although DES models may be used to study a wide range of questions, they appear especially well suited for advancing the quantitative study of ED overcrowding. The predictive capacity of the current EDSIM model performs best when applied to group average patient times, but will require further revision before individual patient times can be predicted with confidence. EDSIM's preliminary comparison of ART and FT approaches shows substantial differences in average patient treatment times that warrant further investigation to more fully characterize the benefits and limitations of each approach.

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