Adding More Beds to the Emergency Department or Reducing Admitted Patient Boarding Times: Which Has a More Significant Influence on Emergency Department Congestion?

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Study objective: We evaluate a computer simulation model designed to assess the effect on emergency department (ED) length of stay of varying the number of ED beds or altering the interval of admitted patient departure from the ED.

Methods: We created a computer simulation model (Med Model) based on institutional data and augmented by expert estimates and assumptions. We evaluated simulations of increasing the number of ED beds, increasing the admitted patient departure and increasing ED census, analyzing potential effects on overall ED length of stay. Multiple sensitivity analyses tested the robustness of the results to changes in model assumptions and institutional data.

Results: With a constant ED departure rate at the base case and increasing ED beds, there is an increase in mean length of stay from 240 to 247 minutes (95% confidence interval [CI] 0.8 to 12.6 minutes). When keeping the number of beds constant at the base case and increasing the rate at which admitted patients depart the ED to their inpatient bed, the mean overall ED length of stay decreases from 240 to 218 minutes (95% CI 16.8 to 26.2 minutes). With a 15% increase in daily census, the trends are similar to the base case results. The sensitivity analyses reveal that despite a wide range of inputs, there are no differences from the base case.

Conclusion: Our computer simulation modeled that improving the rate at which admitted patients depart the ED produced an improvement in overall ED length of stay, whereas increasing the number of ED beds did not. [Ann Emerg Med. 2008;xx:xxx.]

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INTRODUCTION

Background

Crowding in the emergency department (ED) is a global problem.[1-4] There is evidence demonstrating the harmful effects of ED crowding on patient care: increased number of patients who leave without being seen,[5] decreased adherence to recommended therapies for acute myocardial infarction and pneumonia,[6,7] and increased 10-day inpatient mortality.[8] There are several ways of combating ED crowding, including adding functional ED capacity, either by increasing care spaces or changing processes or operations. Given these options, 2 questions arise: Which congestion management strategies are best suited to reduce ED crowding? Can we test potential results before operationalizing either solution?

Importance

The concept of "bottlenecks"—points of operation that restrict performance—is fundamental to addressing the issues of crowding. In the ED, the key bottleneck is the resource or activity in the ED care process that contributes the most to the total time a patient spends in the ED.

Most operational improvements require time and resource investment and are difficult to study in isolation of other interventions. Computer simulation modeling of ED operations could provide an analytical method for studying the process of ED care, identifying bottlenecks, and testing proposed operational and structural interventions to improve ED congestion without directly affecting patient care or requiring significant monetary investment. Computer simulation modeling of ED operations has been promising as a tool for studying ED operational interventions.[9-11]

Editor's Capsule Summary

What is already known on this topic

In theory, emergency department (ED) crowding can be decreased by increasing the number of ED beds or decreasing patient length of stay.

What question this study addressed

Using computer simulation with inputs based on site-specific data and expert opinion, the authors examined whether ED bed number or ED length of stay has a greater effect on crowding.

What this study adds to our knowledge

Throughout a wide range of inputs, this simulation suggests that crowding can be diminished by decreasing ED length of stay by rapidly moving admitted patients to the inpatient setting but not by increased ED bed number.

How this might change clinical practice

For sites whose conditions fall within those used in this study, admission flow improvements will create more real capacity than new physical beds.

Goals of This Investigation

The primary goal of this investigation is to develop and deploy a computer simulation model to evaluate potential bottlenecks and solutions in an ED. We focus on 2 specific ED bottlenecks: (1) the number of ED beds and (2) the rate at which admitted patients depart the ED for an inpatient bed. We evaluate which has a more significant effect on ED length of stay. The secondary goal is to analyze the effect of these findings through sensitivity analyses of model inputs.

MATERIALS AND METHODS

Study Design

We used computer simulation modeling to compare the effect of 2 operational interventions on ED length of stay: increasing the number of ED beds or increasing the rate at which admitted patients leave the ED. We developed the model with a preexisting data set, along with institutional information and expert clinician experience. The study received approval from the Northwestern University Institutional Review Board.

Setting

The computer simulation models an urban, academic, tertiary care, Level I trauma center with an emergency medicine training program that receives more than 75,000 adult ED visits per year. The ED triages patients according to the Emergency Severity Index (ESI) triage system.[12] Patients are then directed to the main ED or urgent care, depending on their ESI category. The main ED has 23 beds and the urgent care area has 7 beds. The ED also manages a 23-bed observation unit on the floor above. During the study period, 3 attending physicians staffed the main ED between 6 AM and 10 PM, and 2 staffed the ED between 10 PM and 6 AM. One additional attending physician staffed the urgent care area between 11 AM and 11 PM. There are 25 ED hallway spaces used for admitted patient boarding. The ED admits 24% of their patients to the hospital and 6% to the observation unit.

Selection of Participants

We used patient ED visit data for February 2006 as the base case, which included 5,751 total ED visits coded as a mean of 205 visits per day. We validated the sampled data used for the base case with census and mean length of stay data from earlier months in the same data set, February 2005 and October 2005. Detailed inputs used in the base case model appear in Figure 1 and Table 1.

To model the flow of patients cared for in the ED, we defined and coded the locations, resources, processes, and routing policies. Second, we focused on the model input requirements as empirical data, estimates, or assumptions based on expert consensus statements.[13,14] Because the main goal of this work is to identify, measure, analyze, and manage our bottlenecks, we made several simplifications when coding the patient flow. For instance, we assumed in the simulation that all urgent care patients are discharged, despite a small number (an average of 2 per day) who were admitted during the study period. These and other assumptions and simplifications are in Figure 1 and Table 1.

Methods of Measurement

The model simulated and tracked ED patients throughout their ED stay, from presentation to discharge home or to an inpatient unit. In Appendix E1 (available online at http://www.annemergmed.com), we review the steps of the patient flow model as seen in Figure 1. This includes details of the model including data used and assumptions made for patient arrivals, triage, waiting area, left without being seen, main ED, urgent care, admission and boarding process, and exiting the ED process.

Outcome Measures

The model output was ED length of stay and served as a marker for ED congestion. Length of stay is defined as the time between sign-in and departure from the ED. Expert consensus recommends ED throughput time (analogous to ED length of stay in our model) as a key measure of ED efficiency and planning.[13]

According to the model inputs specified in Table 1 and Appendix E1 (available online at http://www.annemergmed.com), 4 base case simulations were run through the model, each varying the number of ED beds or the admitted patient departure rate.

- The base case simulated an ED with 23 beds and an admitted patient departure rate of 1 patient leaving the ED from the boarding area to an inpatient bed every 20 minutes.
- A second simulation simulated increasing the number of beds to 28 (5 beds, or 22% increase) while holding the admitted patient departure rate constant at 1 patient every 20 minutes.

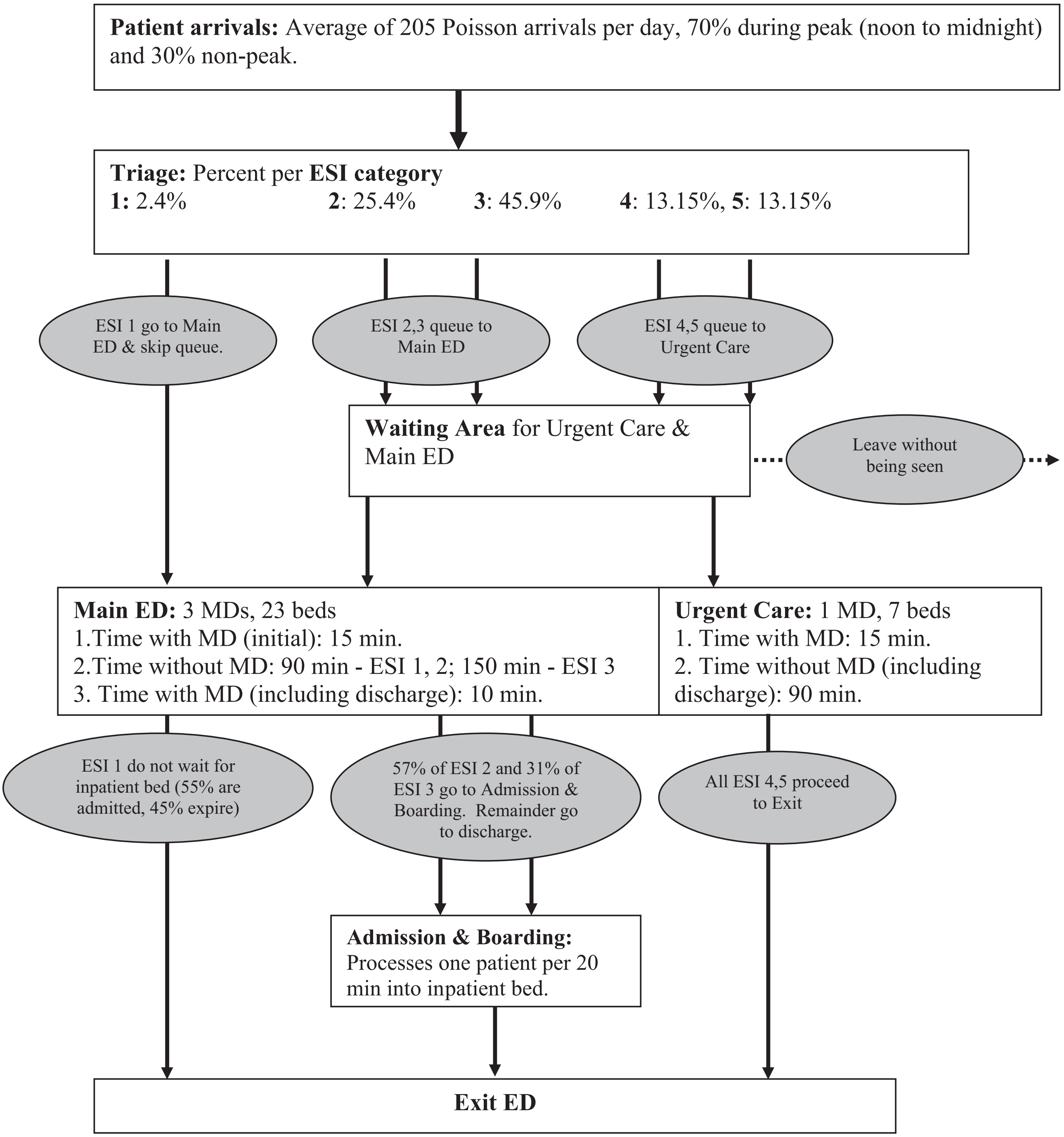


Figure 1. The simulated patient flow dodel with the base case values.

- A third simulation simulated holding the number of ED beds constant at 23 and increasing the rate at which admitted patients depart the ED to 1 patient every 15 minutes (5 minutes, or 25% increase).
- A final scenario simulated 28 ED beds and an admitted patient departure rate of 1 patient every 15 minutes.

Sensitivity Analyses

To test the robustness of the results to changes in model assumptions and actual institutional data, we performed several univariate sensitivity analyses (Table 2):

- Increasing the number of ED beds from 23 to 33 in increments of 5 beds

Table 1. Observed and simulated values for model elements.

Process, Location, or Attribute	Observed Values	Source	Simulated Values	Assumptions
Arrivals	205/day	Census data set	Poisson arrivals, average=205/day	70% of arrivals between noon and midnight
Triage/ESI category	Percentage breakdown per ESI level: 1=2.4%, 2=25.4%, 3=45.8%, 4=13.2%, 5=13.2%	Census data set	Poisson arrivals based on above average and percentage breakdown	Lower ESI values are prioritized throughout the model (ESI 4 seen before ESI 5; ESI 2 seen before ESI 3; ESI 1 seen first).
Waiting area			No preset limit on how many patients can wait for placement in the main ED.	Patients wait if all ED beds are taken. They are moved to an urgent care or main ED bed on a first come, first served basis within their ESI category.
Main ED	23 beds	Institutional information	23 beds	Patients in main ED first see a physician and then wait without physician (for diagnostic testing and treatment), then see a physician again before being admitted or discharged. Times are provided in Figure 1.
	3 attending physicians from 6 AM to 10 PM 2 attending physicians from 10 PM to 6 AM		3 attending physicians	
Observation unit	1 attending physician, 23 beds	Institutional information	Not modeled	Patients admitted to the observation unit are modeled like those admitted to the hospital.
Urgent care	7 beds	Institutional information	7 beds	Patients in urgent care first see a physician, then wait without physician, then are discharged. Times are provided in Figure 1.
	1 attending physician from 9 AM to 9 PM		1 attending physician Always open	
Admission proportion	Percentage admitted per ESI level: 1=55%, 2=57%, 3=31%, 4=1%, 5=1%	Census data set	1=55%, 2=57%, 3=31%, 4=0%, 5=0%	Patient exits ED or is directed to admission according to percentage breakdown.
Admission processing time	61 admissions per day at a rate of 2.5 patients per h (1 per 24 min)	Census data set+institutional information	Admitted patients are processed one at a time, at an average Poisson rate of 3 patients per h (1 per 20 min).	No ESI 4, 5 patients are admitted.
Boarding	25 hallway beds	Institutional information.	No preset limit on how many patients can board	Admitted patients wait in boarding area (hallway) for inpatient bed.
Leave without being seen	3-4%/day	Census data set	25% of ESI 3 leave if not seen by a physician after 90 min; 50% of ESI 4, 5 leave if not seen by a physician after 60 min	

Table 2. Sensitivity analysis for selected elements.*

Process/Location	Data	Origin	Simulation Input/Sensitivity Analysis
Arrivals, total	205/day	Census data set	Base: Assumed to follow a Poisson distribution, with average of 205/day Base+15%: Poisson with average=236/day
Arrivals per ESI Category	Percentage breakdown per ESI level: 1=2.4%, 2=25.4%, 3=45.8%, 4=13.2%, 5=13.2%	Census data set	5% And 10% shifts between ESI=3 and ESI=4, 5: **Base: 1=2.4%, 2=25.4%, 3=45.8%, 4=13.2%, 5=13.2%** Base−5%: **1**=2.4%, **2**=25.4%, **3**=43.6%, **4**=14.3%, **5**=14.3% Base−10%: **1**=2.4%, **2**=25.4%, **3**=41.3%, **4**=15.5%, **5**=15.5% Base+5%: **1**=2.4%, **2**=25.4%, **3**=48.2%, **4**=12.0%, **5**=12.00% Base+10%: **1**=2.4%, **2**=25.4%, **3**=50.5%, **4**=10.9%, **5**=10.9%
Main ED (number of beds)	23 beds	Institutional information	**Base: 23 beds** Base+5 beds: 28 beds Base+10 beds: 33 beds
Main ED (treatment and evaluation times)	ESI 1: 15+**90**+10=115 min ESI 2: 15+**90**+10=115 min ESI 3: 15+**150**+10=175 min ESI 4, 5: 15+**90**=105 min	Institutional information	5% And 10% shift in **treatment and evaluation** times for ESI 2 and 3 **Base treatment and waiting times in minutes for ESI 1=90, 2=90, 3=150, 4=90, 5=90** Base−5%: 1=90, 2=86, 3=143, 4=90, 5=90 Base−10%: 1=90, 2=81, 3=135, 4=90, 5=90 Base+5%: 1=90, 2=95, 3=158, 4=90, 5=90 Base+10%: 1=90, 2=99, 3=165, 4=90, 5=90
Admission proportion	Percentage admitted per ESI level: 1=55%, 2=57%, 3=31%, 4=1%, 5=1%	Census data set	5% And 10% shift for ESI 2 and 3 admission rates **Base: 1=55%, 2=57%, 3=31%, 4=1%, 5=1%** Base−5%: 1=55%, 2=54%, 3=29%, 4=0%, 5=0% Base−10%: 1=55%, 2=51%, 3=28%, 4=0%, 5=0% Base+5%: 1=55%, 2=60%, 3=33%, 4=0%, 5=0% Base+10%: 1=55%, 2=63%, 3=34%, 4=0%, 5=0%
Admission processing time	61 admissions per day=23.6 min per admission	Census data set	**Base: Poisson distribution, average of 20 min per admission** Analyzed: 10, 12.5, 15, 17.5, 20, 22.5 and 25 min per admission
Leave without being seen	3-4%/day	Census data set and expert opinion	Where (x, y) is the probability of x that the patient leaves after waiting y minutes or more for placement into an ED or urgent care bed **Base: (0.25, 90) for ESI=3 and (0.5, 60) for ESI=4, 5** 0%: (0, 90) for ESI=3 and (0, 60) for ESI=4, 5 25%: (0.25, 90) for ESI=3 and (0.25, 60) for ESI=4, 5 75%: (0.75, 90) for ESI=3 and (0.75, 60) for ESI=4, 5 100%: (1.0, 90) for ESI=3 and (1.0, 60) for ESI=4, 5 Base−66.7%: (0.25, 30) for ESI=3 and (0.5, 20) for ESI=4, 5 Base−33.3%: (0.25, 60) for ESI=3 and (0.5, 40) for ESI=4, 5 Base+33.3%: (0.25, 120) for ESI=3 and (0.5, 60) for ESI=4, 5 Base+66.7%: (0.25, 150) for ESI=3 and (0.5, 80) for ESI=4, 5

*The base case values are in bold.

- Varying the admitted patient departure rate from 1 patient every 25 minutes to 1 patient every 10 minutes in increments of 2.5 minutes
- Increasing the daily patient census by 15% to 236, following the same patient arrival distribution as in the base case
- Increasing and decreasing triage level proportions of ESI 3 with ESI 4 and 5 by 10%
- Increasing and decreasing treatment times of ESI 2 and 3 by 10%
- Increasing and decreasing admission rates of ESI 2 and 3 by 10%
- Increasing and decreasing left without being seen rates of ESI 3 with ESI 4 and 5 by 10%

Primary Data Analysis

We used the commercially available software MedModel, version 7.0 (ProModel Corp, Orem, UT) to develop a computer simulation model of the ED. The model simulated a

Table 3. Model validation.*

Model	February 2006	October 2005	February 2005
Daily patient census	**205**	209	204
Actual LOS, min	**273**	251	259
Model LOS, min	**240**	249	237
% Difference in LOS from actual	**−12.1%**	−0.8%	−8.6%

LOS, Length of stay.
*Comparison of model outputs with 3 separate months of institutional data. Bolded area indicates the month on which model inputs and census were developed.

2-week period in the ED, tracking patients through their course of treatment from presentation to the waiting room to discharge home or to an inpatient unit. Methodological details pertaining to the Monte Carlo simulation done for probabilistic sensitivity analysis appear in Appendix E2 (available online at http://www.annemergmed.com).

When testing the effectiveness of an intervention against the base case, we report a 95% confidence interval (CI) for the length of stay difference between 2 means. The midpoint of the interval is the average of the 40 pairwise differences between the modified setting and the base case. The SD is derived from the 40 differences of the modified setting and the base case. We conclude difference when the interval does not cover 0.

RESULTS

We validated the model by comparing model length of stay with actual institution length of stay. Table 3 displays the similarity between daily census and length of stay when comparing the model to 3 months of actual institutional data: February 2006 (base case), October 2005, and February 2005. ED census was similar across each of the 3 months, with the greatest difference being 4 patients, or a 2.0% difference. Model length of stay was also similar to each month's length of stay, with the greatest difference being 33 minutes, or a 12.1% difference.

Table 4A and B displays results of the 4 simulations. When keeping the departure rate constant at 1 patient per 20 minutes and increasing ED beds from 23 to 28, mean length of stay increased from 240 to 247 minutes (95% CI 0.8-12.6 minutes). When keeping the departure rate constant at 1 patient per 15 minutes and increasing ED beds from 23 to 28, there was an increase in mean length of stay from 218 to 225 minutes (95% CI 2.3 to 11.3 minutes).

When keeping the number of beds constant at 23 and increasing the departure rate from 1 patient every 20 minutes to 1 every 15 minutes, there was a reduction in the mean length of stay (Δ 22 minutes; 95% CI 16.8 to 26.2 minutes). When keeping the number of ED beds constant at 28 and increasing the departure rate from 1 patient every 20 minutes to 1 every 15 minutes, there was a reduction in the mean length of stay (Δ 22 minutes; 95% CI 15.8 to 27.1 minutes).

Table 4A. Length of stay with varying the number of ED beds.

Departure Rate/min	23 Beds, min	28 Beds, min	Difference, min	95% CI
1 Patient/20	240 min	247 min	+7	0.8–12.6*
1 Patient/15	218 min	225 min	+7	2.3–11.3*

*Significant: 95% CI for the pairwise differences does not include 0.

Table 4B. Length of stay with varying the admitted patient departure rate.

Departure Rate, No. Beds	1 Patient/ 20 min	1 Patient/ 15 min	Difference, min	95% CI
23	240 min	218 min	−22	16.8–26.2*
28	247 min	225 min	−22	15.8–27.1*

*Significant: 95% CI for the pairwise differences does not include 0.

Figure 2 is the sensitivity analysis of the ED length of stay for a set of ED admitted patient departure rates for an ED census of 205. It also depicts a variation in ED beds (23, 28, and 33 beds) and shows the decrease in length of stay as departure rate increases, regardless of the number of beds. Beyond the results in Table 4A and B, there were no other differences in length of stay observed from varying the number of beds. With a daily census of 205, there was a reduction in mean length of stay when increasing the admitted patient departure rate from 1 every 25 minutes to 1 every 15 minutes in increments of 2.5 minutes for 23-, 28-, and 33-bed settings.

We conducted several other sensitivity analyses to evaluate the effect of altering 4 model inputs on length of stay (Figure 3). The figures show that when altering the daily patient census, admission proportions, acuity levels, treatment times, and there was an ongoing reduction in length of stay when increasing the admitted patient departure rate from 1 every 25 minutes to 1 every 15 minutes in a 23-bed setting across the sensitivity analyses. The same is true for the analysis with an increased ED patient census to 236 when increasing the admitted patient departure rate from 1 every 25 minutes to 1 every 17.5 minutes for 23-, 28-, and 33-bed settings.

Table 5A and B shows the results where the sensitivity analysis testing was the same as the base case analysis, but with a 15% increase in daily patient volume to 236 inputted into the model. The results demonstrate no differences in overall ED length of stay.

Finally, we completed a sensitivity analysis on patients leaving without being seen. We varied both the threshold wait time at which ESI 3 and ESI 4 and 5 patients would wait before leaving the waiting room and the proportion of patients who left without being seen at the base threshold wait time. We found that varying these parameters has little effect on overall length of stay. Holding the threshold wait times at which patients will leave without being seen constant at 90 minutes for ESI 3 patients and 60 minutes for ESI 4 and 5 patients while

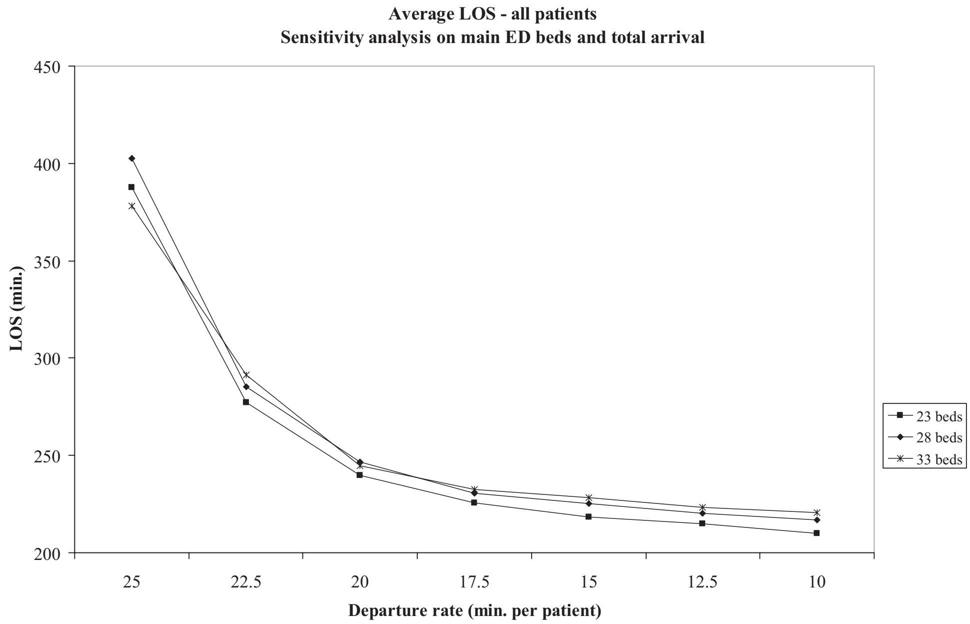


Figure 2. ED length of stay over a set of ED admitted patient departure rates and a variation in ED beds for an ED census of 205.

increasing the proportion who will leave without being seen at those times from 0% to 100% reduced mean length of stay by only 10 minutes (4.1%). Holding the proportion of patients who left without being seen at a given threshold wait time constant at 25% for ESI 3 patients and 50% for ESI 4 and 5 patients increased the mean length of stay by only 8.3 minutes (3.5%).

LIMITATIONS

A computer simulation model is a theoretical instrument based on rules, generalizations, and assumptions. The ability to predict actual outcomes depends on the validity of the assumptions made. We used inputs and assumptions based on institutional data and expert physician experience. These data and assumptions may not be valid in other settings. However, other work supports these assumptions. For example, there is a correlation between waiting room times and ED congestion and leaving without being seen.[15,16]

We also made generalizations and simplifications to the actual institution experience when developing the model. We treated all patients admitted to the observation unit as if they were admitted to the hospital. The model was developed with as much actual institutional data as possible but, for example, during the study time period patient boarding times were not captured. Therefore, in the model we used total ED length of stay as a marker for congestion and an indirect indicator of boarding time. We also used the admitted patient departure rate as an indirect method of changing the amount of time that patients board in the ED. We presumed that by increasing the rate at which admitted patients depart the ED we are decreasing the boarding times. While necessary for modeling a complex environment, these generalizations, simplifications, and indirect measures may limit the scope of our results.

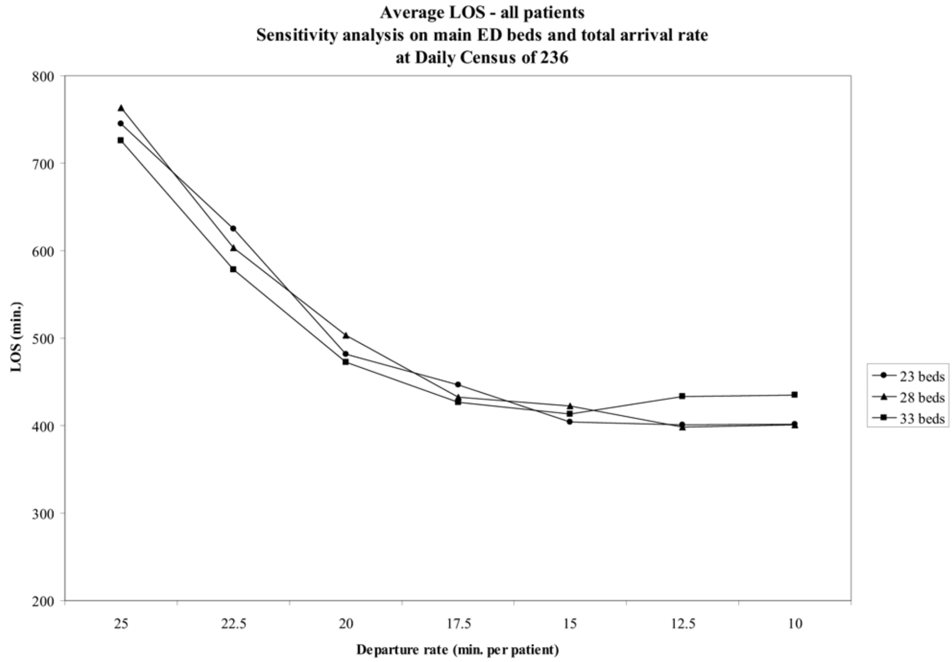
When making model generalizations and simplifications, one must remember that the model is not a perfect fit to the actual ED: there was a 33-minute or 12.1% difference in length of stay between modeled and observed data. We still believe the model allows estimation of effects even if discrete values vary from actual.

Although the results presented here are based on institutional data, our model is based on 1 ED. Other sites may experience different characteristics and require specific inputs to measure results in their institution.

DISCUSSION

Our simulation allows the effect of ED bottleneck intervention to be assessed. In this ED, the admitted patient departure rate is the key bottleneck. If alterations are made in other areas first, ED length of stay and congestion will likely be only marginally affected. Recent data confirm the paradox that a bigger ED alone did not improve—and actually worsened—ED length of stay and admitted patient boarding times.[17]

Understandably, many concepts in operations research seem counterintuitive. On first glance, it would seem that adding ED beds would allow a department to treat more patients quickly by decreasing waiting room times. However, when increasing the number of patients processed through the ED without



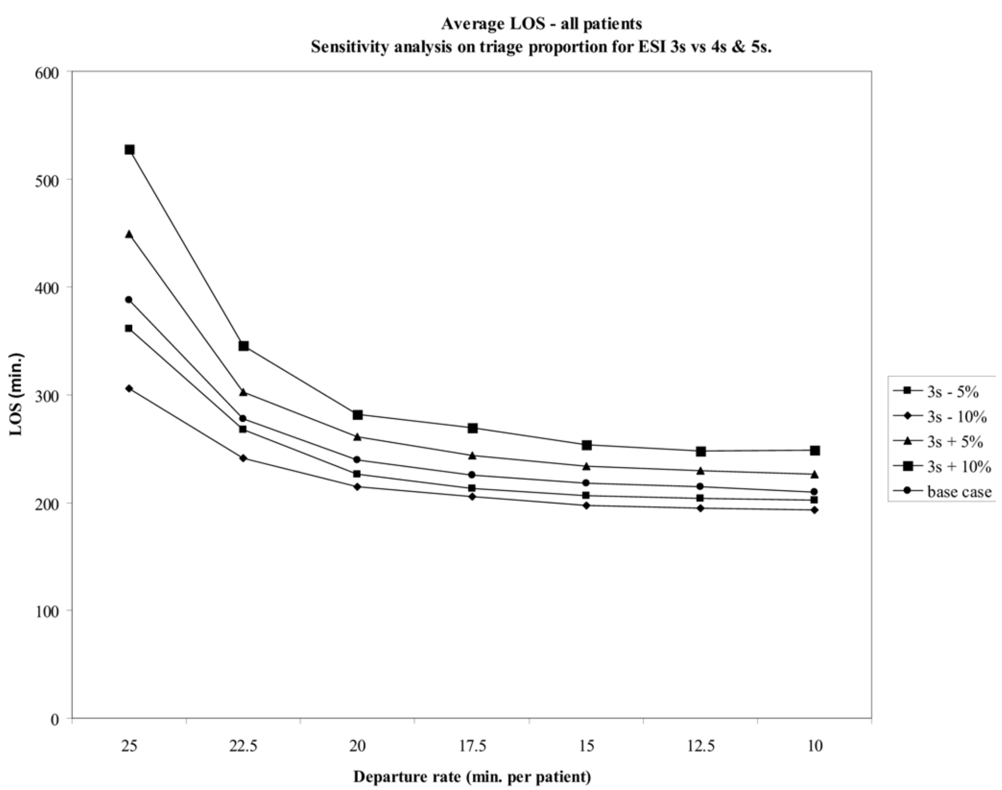


Figure 3. Sensitivity analysis. Effect of length of stay on altering model inputs over different number of beds and a range of patient departure rates.

increasing the rate at which patients depart the ED, length of stay remains the same or increases. In an analogous manner, one can imagine the ED to be a pipe and patients as water passing through the pipe. If we enlarge the diameter of the middle of the pipe but leave the end the same, we analogously have increased the number of ED beds without improving the departure rate.

Researchers have proposed methods that coordinate hospital census and drivers of inpatient congestion with ED patient outflow. Litvak et al proposed that the artificial

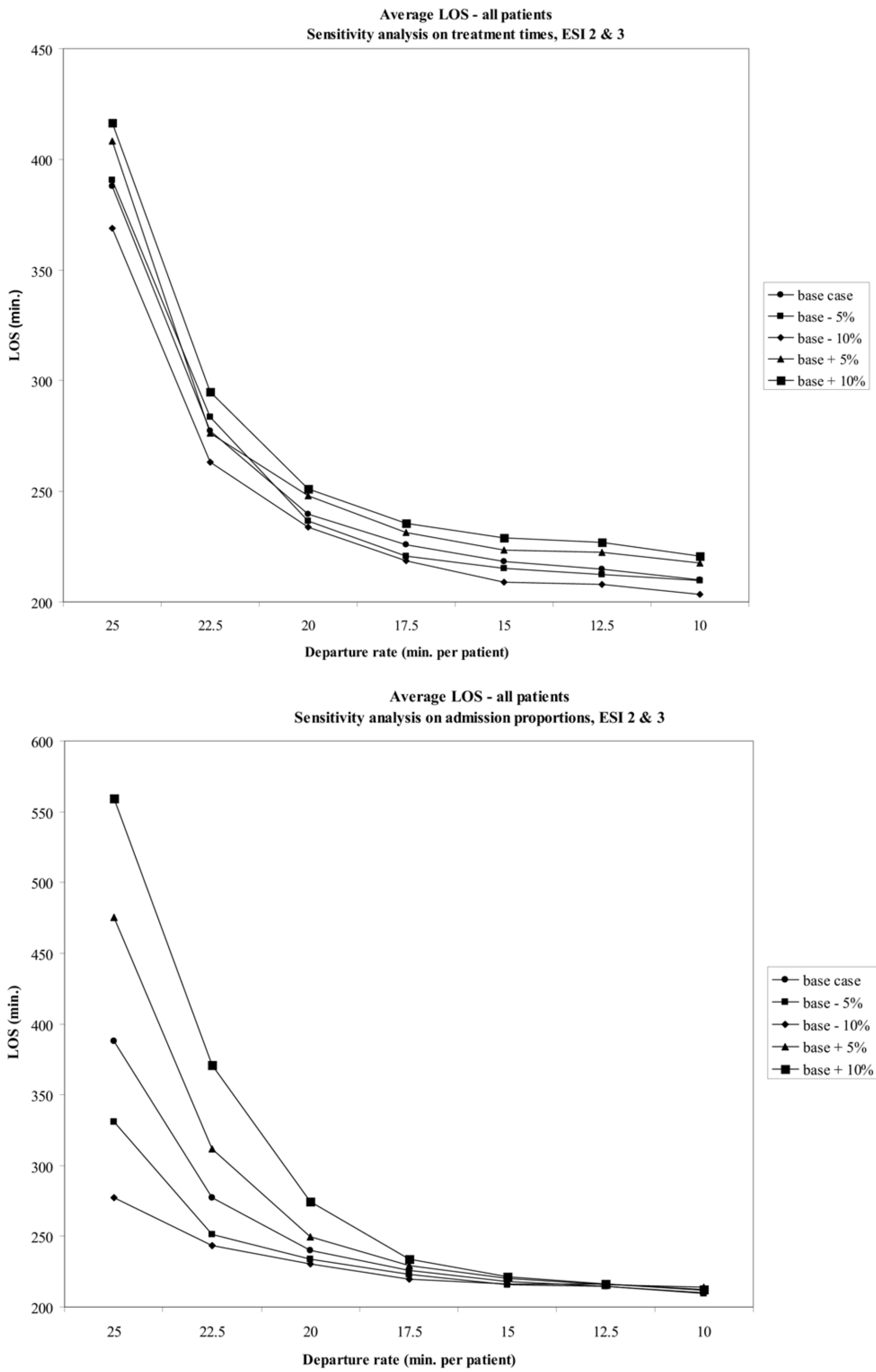


Figure 3. Continued.

variability of elective surgery scheduling and elective inpatient admissions affect inhospital congestion, and a decrease in this variability would improve ED output and subsequently ED congestion.[18] Others have reinforced these concepts by showing a correlation between hospital occupancy and ED length of stay,[19] as well as a correlation between increased scheduled elective surgeries and ED length of stay.[20] Some have proposed that boarding admitted patients outside the confines of the ED, in the inpatient hallways, would be a better solution to long inpatient boarding times in the ED.[21,22] All aforementioned strategies decrease the amount of time patients spend boarding in the

Table 5A. Length of stay with varying the number of ED beds at a 15% increase in daily patient census.

Departure Rate/min	23 Beds	28 Beds	Difference, min	95% CI
1 Patient/20	482 min	504 min	+22	−22.3 to 66.4
1 Patient/15	404 min	422 min	+18	−59.8 to 24.1

Table 5B. Length of stay with varying the admitted patient departure rate at a 15% increased daily patient census.

Departure Rate	1 Patient/ 20 min	1 Patient/ 15 min	Difference, min	95% CI
23 Beds	482 min	404 min	−78	33.3–121.1*
28 Beds	504 min	422 min	−82	36.9–125.8*

*Significant: 95% CI for the pairwise differences does not include 0.0

ED, decrease ED length of stay, and free ED bed space to treat new patients in need of care, an opportunity lost otherwise.[23]

By modeling our ED through computer simulation, we show that improving the rate at which admitted patients depart the ED produced an improvement in ED length of stay and therefore congestion, whereas increasing the number of ED beds did not.

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Editor's Capsule Summary: *What is already known on this topic:* In theory, emergency department (ED) crowding can be decreased by increasing the number of ED beds or decreasing patient length of stay. *What question this study addressed:* Using computer simulation with inputs based on site-specific data and expert opinion, the authors examined whether ED bed number or ED length of stay has a greater effect on crowding. *What this study adds to our knowledge:* Throughout a wide range of inputs, this simulation suggests that crowding can be diminished by decreasing ED length of stay by rapidly moving admitted patients to the inpatient setting but not by increased ED bed number. *How this might change clinical practice:* For sites whose conditions fall within those used in this study, admission flow improvements will create more real capacity than new physical beds.

APPENDIX E1. Patient arrivals.

The average number of patients who presented to the ED in February 2006 was 205 per day, 70% of whom presented during the peak hours, which extend from 11 AM to 11 PM. To simplify coding, we assumed a noon to midnight peak period in the model. To mimic actual ED arrival distribution, arrivals are generated following a Poisson distribution, meaning that the likelihood of an arrival in a specified interval is independent of the arrival times of the previous patients. On patient entry into the model, the system stores a set of attributes for each patient, one of which is the arrival time, which will be used to compute intermediate processing and waiting times, along with average length of stay statistics.

Triage

The simulated patient then moves to triage, where each modeled patient is assigned an ESI category based on the distribution observed in February 2006, which is detailed in Figure 1. Throughout the remainder of their stay, patients will be prioritized or routed to care according to that ESI category. In the simulation, patients are seen in the order defined by their ESI category first (with lowest ESI category being given highest priority) and in their order of arrival within each category second. We assume that all patients assigned an ESI 1 category proceed directly to a main ED bed, whereas ESI 2 and 3 patients proceed to the waiting area. If a bed is available, the next patient in the waiting area proceeds to it. When all 23 beds are occupied, ESI 2 and 3 patients remain in the waiting area until one of the 23 beds becomes available. In the urgent care, when all 7 beds are occupied, ESI 4 and 5 patients remain in the waiting area until one becomes available.

Waiting Area

There are 2 waiting areas in the simulation, one for the main ED (ESI 2 and 3 patients) and one for urgent care (ESI 4 and 5 patients), each with no limit on the number of patients it can accommodate.

Left Without Being Seen

While waiting for a bed, some patients may opt to leave without being seen by a physician. In February 2006, 7.75 per day, or 3.8% of patients who presented to the ED, left without being seen. To model this flow in the simulation, we developed rules for ESI 3, 4, and 5 patients and assumed that no ESI 1 or 2 patients left without being seen. The exact motivation behind the decision to leave without being seen is complex to model because it is ultimately a patient-based decision based on a number of factors. It has been demonstrated that there is a direct correlation between ED overcapacity and leaving without being seen.[1] According to trends published in the literature and the authors' experiences, we modeled the decision with 2 factors: a probability of a patient leaving without being seen per ESI level and a threshold time (how long the patient will wait before leaving without being seen). Specifically, we assumed that 25% of ESI 3 patients left if not placed into a bed within 90 minutes of presenting to the ED, and 50% of ESI 4 and ESI 5 patients left if not placed into an urgent care bed within 60 minutes of presenting to the ED.

Main ED

In the simulation, the main ED consists of 23 beds, 3 attending physicians, and a hallway area consisting of 25 boarding spaces. Once a patient with an ESI of 1, 2, or 3 occupies a main ED bed, the simulated process is broken down into 3 steps. First, the patient spends 15 minutes with a physician for an initial assessment and may have to wait if all 3 physicians are busy with other patients. Then ESI 1 and 2 patients spend 90 minutes without the physician, whereas ESI 3 patients spend 150 minutes without the physician, during which time treatment and diagnostic tests are conducted. Note that nursing, ancillary staff, consultant time, laboratory, and radiology resources are not specifically modeled but are included in this treatment time. Finally, the patient spends 10 more minutes with the physician before being admitted or discharged. This results in treatment times of 115 minutes for ESI 1 and 2 patients and 175 minutes for ESI 3 patients. The partial figures were derived from actual length of stay data, combined with knowledge of standard evaluation times. These times do not include boarding time, which we define as the amount of time admitted patients spend in the hallway while awaiting an inpatient bed.

Urgent Care

The urgent care area has 7 beds and 1 attending physician and consists of ESI 4 and 5 patients. Once in urgent care, the simulated patient spends 15 minutes with the attending physician and may have to wait if the physician is busy with other patients. Then the patient spends 90 minutes without the physician, undergoing diagnostic and therapeutic interventions. This includes nursing, ancillary, consulting and laboratory resources. This results in treatment times of 105 minutes for ESI 4 and 5 patients. The partial figures were derived from actual length of stay data, combined with knowledge of standard evaluation times. We do not model the rare patients who are admitted from the urgent care; therefore, in the model, all urgent care patients are discharged after treatment.

Admission and Boarding

The proportions of ESI 1, 2, and 3 patients who were routed to admission and boarding in the simulation were based on actual percentages observed in February 2006. For ESI 2 patients, 57% proceed to admission and wait for an inpatient bed, whereas 43% are discharged and proceed to exit the ED. For ESI 3 patients, 31% proceed to admission and wait for an inpatient bed, whereas 69% are discharged and proceed to exit the ED. If an inpatient bed is not available, patients will board and thus occupy a hallway space until a bed becomes available in the appropriate inpatient unit. For ESI 1 patients, 55% proceed to exit the ED into an inpatient bed and bypass boarding because of their severity index. The remainder also proceed to exit the ED, either by being discharged or having died. Death is not modeled.

Because inpatient units are outside the scope of the ED, and because there is significant unpredictability in how inpatient beds become available, we assumed for the base case that patients were processed out of admission and boarding according to a Poisson distribution, with an average of 1 patient every 20 minutes. The actual rate is 1 patient per 23.6 minutes, or 61 patients per day. We model a slightly faster rate in our base case to factor in the lower waits during nonpeak hours.

Exit ED

All admitted or discharged simulated patients leave the system through this location where visit data were saved and aggregated.

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APPENDIX E2.

A discrete-time Monte Carlo simulation generates a list of time epochs in minute units: 1, 2, 3. . . 21,600, where the last number represents 15 days. Statistics are collected from days 2 to 15. Day 1 is considered a warm-up period in which no model output is used for analysis. This is done to prevent the simulation from reporting modeled data statistics before the system has reached steady state and minimizes the potential bias from the system being empty at the onset. The simulation then generates sets of random numbers based on actual data, distributions, and other information provided. These capture the process randomness such as arrivals into the ED, wait times, and other patient characteristics. According to routing and other model assumptions, they are then matched to the time epochs to effectively simulate the process of patients traversing the ED and to derive statistics that help quantify the process and test the effect of potential interventions.

Each random stream is seed specific and based on the algorithms described by Law and Kelton.1 A seed is the initial value fed into the random-number generator, and seed specific implies that each replication starts with a different initial value and therefore generates a different output for each 2-week replication. Each data point reported represents an average during 40 replications of a 14-day horizon. The standard deviation during the 40 points is used to estimate the width of the associated 95% CI. Using 40 replications allows us to balance statistical precision (sufficient degrees of freedom for the central limit theorem to apply) with efficiency (1 data point takes an average of 3 minutes to generate on a Genuine Intel CPU T2600 at 2.16GHz [Santa Clara, CA], operating on Windows XP Professional [Redmond, WA]).

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