

Analysis and Optimization of the Emergency Department at Beth Israel Deaconess Medical Center via Simulation

by

Clay W. Noyes

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Author
Sloan School of Management
Interdepartmental Program in Operations Research
May 15, 2008

Certified by.....
Francis Carr
Charles Stark Draper Laboratory
Technical Supervisor

Certified by.....
Dimitris Bertismas
Boeing Professor of Operations Research
Thesis Supervisor

Accepted by.....
Cynthia Barnhart
Professor of Civil and Environmental Engineering
Codirector, Operations Research Center

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Abstract

We develop a simulation model based on patient data from 2/1/05 to 1/31/06 that represents the operations of the Emergency Department at Beth Israel Deaconess Medical Center, a Harvard teaching hospital and a leading medical institution. The model uses a multiclass representation of patients, a time-varying arrival process module that uses multivariate regression to predict future patient arrivals, and a service module that takes into account the fact that service times decrease and capacity increases when the system becomes congested. We show that the simulation model results in predictions of waiting times that closely match those observed in the data. Most importantly, we use the simulation model to propose and analyze new policies such as increasing the number of beds, reducing the downtime between patients, and introducing a point of care lab testing device. The model predicts that incorporating a suite of these proposed changes will result in 21% reduction in waiting times.

Technical Supervisor: Francis Carr
Title: Senior Member of the Technical Staff

Thesis Supervisor: Dimitris Bertismas
Title: Boeing Professor of Operations Research

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Clay W. Noyes

2nd Lieutenant, USAF

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2nd Lieutenant, USAF

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Chapter 1

Introduction

The Emergency Department (ED) of the Beth Israel Deaconess Medical Center (BIDMC) has invested in creating a “Dashboard” software system. The data underlying the Dashboard is an accurate, thorough and real-time representation of the status of the ED, including information about patients in the ED and about ED resources such as staff and beds. Such complete and reliable data has provided opportunity for in-depth analyses of ED operations and exploration of possible improvements.

The purpose of this thesis is twofold. The first goal is to present a model of the ED operations for performance analysis. This model includes the arrival rates of new patients to the ED, the “flow dynamics” once patients arrive, and the length-of-stay and impact on ED resources of current ED patients. This modeling effort relies on the expertise of ED staff and on the analyses of 1 year of anonymized Dashboard data provided by BIDMC. The second goal is to propose policies for improving the “flow management” of the ED and evaluate them using a Monte Carlo simulation model.

We have evaluated four such policy changes: adding extra beds to allow greater capacity in the ED; an improved bed “flip” policy which reduces the time spent cleaning beds between patients; a new “Point of Care” (POC) lab test for troponin which promises to greatly reduce the time in the ED for patients with chest pain symptoms; and a “nested bed policy” which reserves some ED bed capacity in anticipation of the possible arrival of more acute patients.

Simulation results indicate that adding an extra bed, reducing the bed “flip” time,

and introducing a POC troponin test can significantly reduce patient waiting times and overall patient length of stay. Additionally, reserving an extra bed for more acute patients can reduce waiting times for these classes of patients at the expense of increased waiting times for the less acute patients. The simulation model gives ED staff the capability to evaluate this and other proposed policy changes to determine tradeoffs and seek improvements to current operations.

Simulation analysis of hospital and emergency department operations is not new. Hancock and Walter [13] first applied simulation to hospital systems to improve scheduling of staff, admissions, and surgery. Saunders et al. [20] sought to quantify the effect that the number of physicians, nurses, and beds had on patient throughput time. Jun et al. [15] present a survey of discrete-event simulation in health care clinics. Kim et al. [16] utilize actual data from a hospital's intensive care unit to analyze the policies for admission and discharge of patients. Harper [14] provides a framework for modeling hospital resources and discusses using simulation to develop more sophisticated hospital capacity models. Connelly and Bair [8] use simulation to compare two different patient triage methods in an emergency department. Blasak et al. [5] and Samaha et al. [19] present separate simulation models to evaluate possible alternatives for reducing length of stay in an emergency department. Komashie and Mousavi [17] use discrete-event simulation to model an emergency department and explore waiting times. Cochran and Bharti [7] present a stochastic model of the "flow" of patients to and from various hospital departments and use discrete-event simulation to maximize "flow" through the system. Duguay and Chetouane [9] use discrete-event simulation to reduce patient waiting times and improve throughput by adding resources.

Additionally, a McCallum Graduate School team from Bentley College has analyzed one year of ED data from BIDMC in order to identify process inefficiencies and recommend solutions with the goal of reducing patient throughput time [10]. In this thesis we use simulation analysis to further evaluate the proposals of the Bentley team and quantify the impact that these and other proposals will have on ED operations at BIDMC.

The outline of this thesis is as follows. In Chapter 2, we present the simulation model including the relevant parameters, all of which are based on available data. In Chapter 3, we validate the simulation model by comparing simulation results to the actual data. In Chapter 4, we propose and evaluate policy changes. In Chapter 5, we consider further extensions to our work. Chapter 6 contains our conclusions.

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Chapter 2

Simulation

In this chapter, we develop a model of the arrival and “flow” of patients through the ED at BIDMC. We begin by describing the available data and basic observations, and then develop the relevant parameters for each module of the model.

2.1 Data and Basic Observations

Each patient in the ED at BIDMC goes through a series of processes including triage, registration, waiting in the waiting room, bed assignment, assignment to one or more nurses, residents, and attending physicians, lab tests, radiology exams, diagnosis, treatment, and admission or discharge. In general, relevant information about each of these processes is recorded in the Dashboard data collection system, including a timestamp for when it occurs or when it starts and ends.

The first such timestamp occurs immediately upon each patient’s presentation to the ED. Once the patient undergoes triage, more information is recorded, including severity or acuity level on a scale of 1-5, also known as the Emergency Severity Index (ESI). When a patient is registered, important information about the patient is also recorded including a visit number, a permanent patient number, their date of birth, and their chief complaint.

Several timestamps occur simultaneously when a patient leaves the waiting room. Timestamps record when the patient leaves the waiting room, when the patient is

placed in a bed, and when the patient is seen by a nurse, a resident, and an attending physician. The bed number is also recorded.

As the patient undergoes diagnosis and treatment, the Dashboard records information about which labs and radiology exams are ordered, when they are ordered, when they are processed, what the results are, and when the results became available to the patient's clinicians. The system also records the final disposition of the patient (usually admitted or discharged but occasionally something else) and the final diagnosis/diagnoses, which are encoded using the standardized International Classification of Diseases (ICD). The Dashboard records when an inpatient bed is requested for patients who will be admitted, when that bed is assigned, and when that patient is finally admitted. It also records when each patient leaves the ED (whether to be discharged, admitted, or transferred, etc.).

BIDMC has provided patient visit data for all visits to the ED from 2/1/05 to 1/31/06. This includes 47,537 patients. Also included in the data is the status/utilization of ED resources in 10 minute time-slices.

Based on analysis of the available data and discussion with ED staff, we have chosen to model ED operations with beds as the critical resource and ESI or triage level as the primary method to distinguish patient type. We also considered a model of the ED with nurses as the critical resource. However, beds seemed to be the most critical resource based on the frequent overcrowding in the ED and the use of temporary hallways spaces to try to accommodate patient demand. Furthermore there was no significant correlation in the data between additional nurses and faster service times. We also considered separating the patients based on final disposition (admit or discharge or observation) or final diagnosis (clusters of ICD codes), but ESI level proved to be the most relevant way to classify patients, especially considering that bed assignment priority is generally based on patient ESI level.

The model (Figure 2-1) used to analyze ED operations consists of 5 processes: arrival, triage and registration, waiting in the waiting room, diagnosis and treatment, and exit. We will now discuss each of these processes.

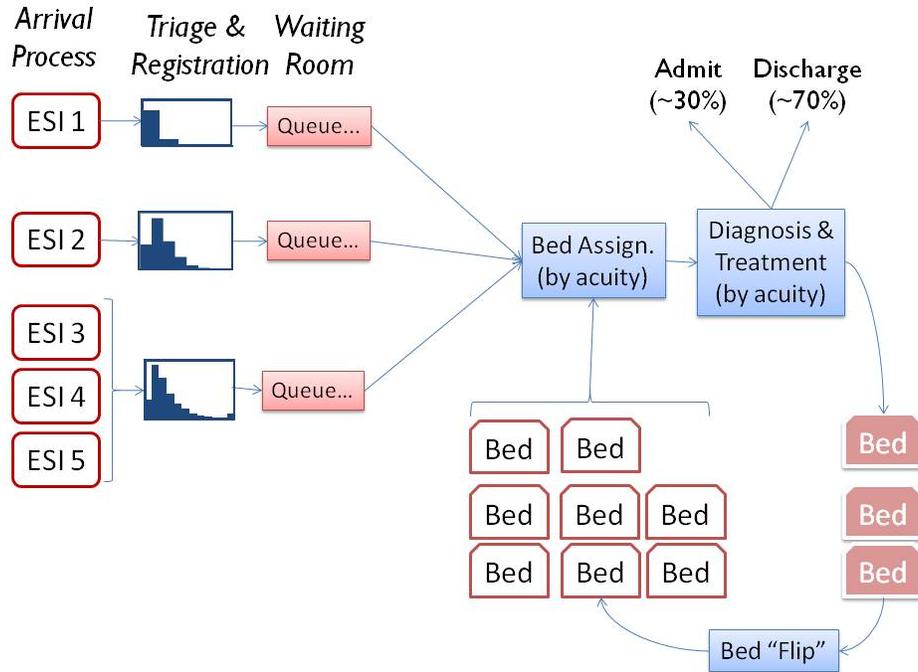


Figure 2-1: BIDMC Emergency Department Simulation Model.

2.2 Arrival Process

One of the main challenges faced by emergency departments is the fluctuating nature of arrivals. While patient demand is often predictable there are occasional surges which stretch resources beyond capacity and leave hospital staff feeling overworked and hospital patients feeling neglected. Researchers have identified emergency department crowding as a major barrier to receiving timely emergency care in the United States [1]. It is also on the busiest days that patient waiting times reach their highest levels. In order to perform reliable analysis of ED operations, it is necessary to incorporate in the model an accurate estimate of patient arrival rates which accounts for these fluctuations.

Table 2.1 shows the results of linear regression analysis to predict the number of arrivals to the ED in 8 hour blocks. Using a random 70 percent of the data points to generate the model, the resulting value of R^2 is 0.84. Using the remaining 30 percent of the data to test the model, the R^2 value is 0.84 (Table 2.2). Results of the regression indicate that time of day has the greatest impact on the arrival rate. The

period from 8 am to 4 pm is the busiest period of the day in terms of arrivals while the period from midnight to 8 am is the slowest. Arrivals are observed to occur more frequently on weekdays than on weekends, and there is a positive correlation between the arrival rate at a given point in time and the number of arrivals that occurred between 48 and 96 hours prior to that moment.

Table 2.1: Demand Prediction Linear Regression Analysis.

Variable	Estimate	Std.Err.	t-Statistic
(Intercept)	28.99	3.42	8.49
Time of Day (midnight to 8 am)	-24.66	0.4	-61.61
Time of Day (8 am to 4 pm)	17.55	0.4	44.06
Time of Day (4 pm to midnight)	7.11	0.41	17.4
Day of Week (Weekend)	-1.93	0.31	-6.14
Day of Week (Weekday)	1.93	0.31	6.14
Number Arrivals 48-96 hours earlier	0.05	0.01	4.14

Table 2.2: Demand Prediction R-Squared.

Data Set	R^2
Training Data (70 percent)	0.84
Test Data (30 percent)	0.84

The model in Table 2.1 is what we consider our best model because of its simplicity and high correlation to historical data. Several other models were considered with various combinations of the variables used above and the following variables which were not used in our best model:

- Time of Day in 1 hour blocks
- Time of Day in 6 hour blocks
- Time of Day in 12 hour blocks
- Time of Day in 24 hour blocks
- Day of Week (Mon, Tues, Wed, Thurs, Fri, Sat, Sun)

- Day of Week (Monday, Midweek, Friday, Saturday, Sunday)
- Number of Arrivals 0-4 days earlier in 8 hour blocks
- Number of Arrivals 0-4 days earlier in 12 hour blocks
- Number of Arrivals 0-4 days earlier in 24 hour blocks
- Holiday
- Temperature and Precipitation

The arrival rates used in the simulation model are generated from the linear regression analysis in Table 2.1. Within each 8 hour block there is an arrival rate predicted by the linear regression coefficients based on time of day, day of week, and previous arrivals. Patient inter-arrival times within this 8 hour block are sampled from an exponential probability distribution at the prescribed arrival rate.

To further clarify how arrivals are sampled in the Monte Carlo simulation based on the model, it is helpful to understand how the simulation clock functions. At a given time within the simulation, the arrival rate is predicted based on time of day, day of week, and previous arrivals. The units for time within the simulation are hours, and the simulation clock is initialized at midnight on a Monday. The time of day and day of week are computed using the modulus function. These indicator variables determine which coefficients are used from Table 2.1 to calculate the arrival rate. The previous arrivals variable is computed by looking at the current simulation time and counting the number of arrivals that occurred between 48 and 96 hours prior to that moment. The number of previous arrivals is multiplied by the appropriate coefficient and added to the intercept coefficient and appropriate time of day and day of week coefficients to calculate the arrival rate. Inter-arrival times are then generated from an exponential distribution according to the calculated rate.

2.3 Service Times

There are three different aspects of service that occur in the model: the triage process, diagnosis and treatment, and the bed cleaning or “flip.” In this section we discuss each of these aspects and how they are represented in the model.

2.3.1 Triage Times

It is during triage where the ESI or acuity level is determined for each patient. This index helps give ED staff an estimate of the resources a patient will require as well as the priority in which the patient should be seen. Patients classified as ESI-1 are the most acute patients and require immediate attention. Patients classified as ESI-5 are the least acute and can safely wait many hours to be treated. Table 2.3 shows the number and percentage of arrivals for each ESI level from 2/1/05 to 1/31/06.

Table 2.3: Patient Acuity (1 = Most Acute, 5 = Least Acute).

	Number of Arrivals	Percentage of Patients
ESI-1	1165	2.45%
ESI-2	10910	22.95%
ESI-3	28372	59.69%
ESI-4	6756	14.21%
ESI-5	332	0.70%
Total	47535	100.00%

Although triage times were not explicitly captured in the Dashboard, there was one timestamp when each patient presented to the ED, and another timestamp when each patient left the waiting room. Triage occurred at some point between these two timestamps and although not all of this time was necessarily spent in triage (much of the time is often spent waiting for an available room or nurse), we presume that the time patients spent “waiting” when no other patients were in the waiting room is very likely to have been time spent in triage. (It is possible to recreate from the data the number of patients already waiting in the waiting room when each patient arrived.) Triage times were therefore estimated to be the time patients spent waiting to leave the waiting room (i.e., time from presentation until leaving waiting room) when the waiting room was empty upon their arrival. Table 2.4 summarizes these triage time statistics. The average triage time per patient is 15.4 minutes. This time is lower for more acute patients who are often rushed into a bed immediately upon arrival.

Table 2.4: Triage Time Distribution (minutes).

	All Patients	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
Mean	15.4	2.1	8.0	17.0	22.4	20.0
Standard Deviation	19.9	8.6	9.8	21.1	23.3	16.2
99 th Percentile	96.0	41.9	44.0	102.1	116.8	68.7
95 th Percentile	51.0	11.9	26.0	53.0	66.8	50.4
90 th Percentile	36.0	1.0	19.0	39.0	50.0	41.1
75 th Percentile	20.0	0.0	11.0	22.0	29.0	25.8
50 th Percentile	9.0	0.0	5.0	11.0	15.0	16.5
25 th Percentile	4.0	0.0	1.0	5.0	8.0	8.0
10 th Percentile	0.0	0.0	0.0	1.0	4.0	5.0
5 th Percentile	0.0	0.0	0.0	0.0	2.0	3.7
1 st Percentile	0.0	0.0	0.0	0.0	0.0	2.1

2.3.2 Waiting Room Policy/Priority

Patients of ESI-1 are given first priority to leave the waiting room when rooms become available. ESI-2 patients are given the next priority. ED policy states that ESI-3 patients would have next highest priority, followed by ESI-4 and ESI-5. However, the data shows that often the less acute patients (ESI-3, 4, and 5) are not necessarily seen in order of priority, and in fact are often assigned beds on a first-come first-serve basis (FCFS) regardless of their relative ESI. The model incorporates this latter strategy, as depicted in Table 2.5.

Table 2.5: Waiting Room Priority.

Acuity Level	Priority
ESI-1	Highest
ESI-2	2 nd Highest
ESI-3	Lowest-FCFS
ESI-4	Lowest-FCFS
ESI-5	Lowest-FCFS

Based on on-site ED observations and informal interviews with ED staff, it became clear that although beds are assigned to patients based on ESI classification, with the more acute patients receiving higher priority than less acute patients, these classifications are not always absolute. For example, occasionally a patient will be classified as ESI-2, but because the symptoms may stabilize, that patient may not be assigned a bed until after several ESI-3 patients. Also, because triage is done quickly and prior to more detailed diagnosis, it is not uncommon for patients to be triaged incorrectly, i.e., lower or higher than their condition is later found to warrant.

We have chosen to use a small amount of randomization in the model to help approximate this effect on the bed assignment priorities. Because the Dashboard system does not record ESI misclassifications, we have estimated that approximately 2% of ESI-1 and ESI-2 patients may have been misclassified.

2.3.3 Diagnosis and Treatment

Currently at BIDMC there are 46 rooms in the ED. One room is reserved for severe trauma patients and the remaining 45 rooms can be used by patients of any ESI. Technically the rooms of the ED are divided into zones with special purposes such as observation, fast track, or acute zones. However, each room can be used for treating any type of patient. For the model all rooms are considered equal, with the exception of one room reserved for the acute ambulance arrivals. Although in reality patients can be and often are reassigned from room to room, for the simulation a patient is assigned to one room only and eventually departs from the originally assigned room. Note that this simplification does not affect the role of rooms as a limiting resource in the ED.

Bed times are explicitly recorded in the Dashboard system and the statistics of these times are used in the model (Table 2.6). Although ESI-1 patients have the most serious conditions and require the most ED resources, they have shorter bed times than ESI-2 and ESI-3 patients because they are almost always given inpatient beds immediately when admitted to the hospital. Other less acute patients generally have to wait much longer to be admitted from the ED into the hospital. ESI-4 and

ESI-5 patients have the shortest average bed times simply because their conditions are usually so minor that they can be treated quickly and discharged.

Table 2.6: Bed Time Distribution (hours).

	All Patients	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
Mean	6.46	5.69	8.41	6.63	2.95	1.85
Standard Deviation	5.77	4.47	6.27	5.70	3.24	1.92
99 th Percentile.	27.75	22.43	30.00	27.51	18.52	11.46
95 th Percentile	18.80	14.98	22.32	18.90	7.89	4.71
90 th Percentile	13.12	11.80	16.70	13.37	5.37	3.45
75 th Percentile	8.08	6.99	9.82	8.23	3.35	2.28
50 th Percentile	4.90	4.47	6.69	5.06	2.17	1.42
25 th Percentile	2.73	2.78	4.62	2.98	1.35	0.77
10 th Percentile	1.48	1.71	3.12	1.73	0.75	0.33
5 th Percentile	0.93	1.07	2.27	1.07	0.40	0.13
1 st Percentile	0.05	0.21	0.73	0.03	0.00	0.00

2.3.4 Patient Exit/Bed “Flip”

Historically at BIDMC, approximately 65% of ED patients are discharged while approximately 30% are admitted. (The rest are transferred, leave before receiving full treatment, or otherwise exit the system.) Because the model is restricted to the ED and not the entire hospital, when a patient exits he or she simply vacates the assigned bed and leaves the system. After the bed/room is cleaned it becomes available for the next patient.

Bed cleaning times are not explicitly recorded by the Dashboard system. There is data available for when beds are occupied versus how long beds sit empty. The bed cleaning or “flip” time must therefore be some portion of the time the bed sits empty. In order to estimate the bed “flip” times we presume that when the ED is very busy (i.e., many people in the waiting room) the bed “flip” process will begin as soon as the bed is vacated and once the bed “flip” is complete, the highest priority patient

will be immediately assigned to the now available bed. Figure 2-2 plots the mean, median, and standard deviation for the empty bed times versus number of patients in the waiting room for the core zone beds, which are the most commonly used beds in the BIDMC ED.

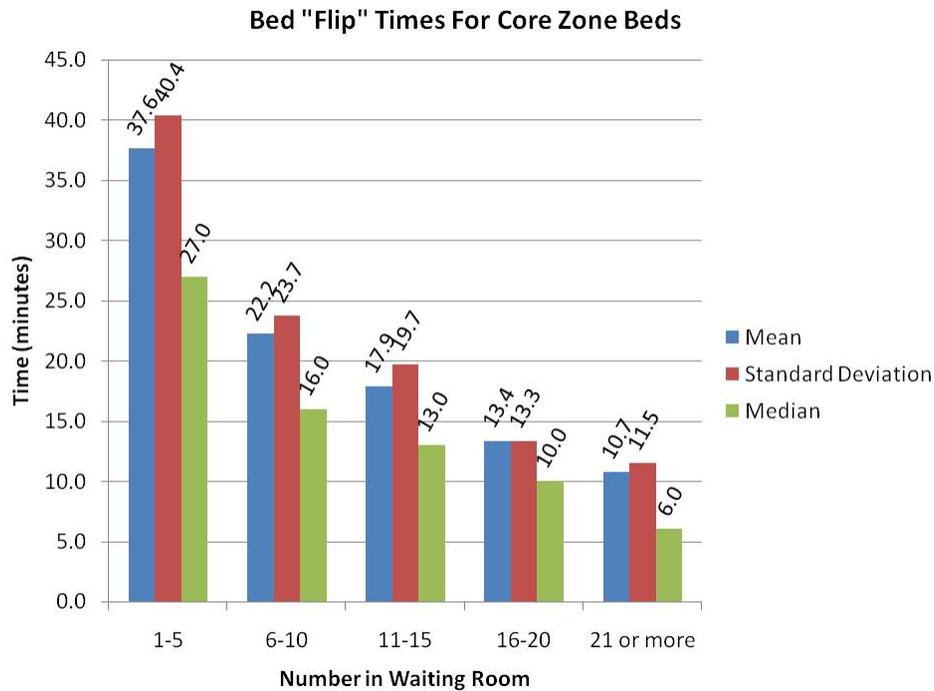


Figure 2-2: Empty Bed Times versus Number of Patients in Waiting Room.

It was interesting to discover that as pressure mounts on the system, the time that beds sit empty decreases. This may indicate that the work rate increases and beds are cleaned faster as the number of people in the waiting room grows large, or simply that as more people arrive they are placed in beds faster.

For the simulation, the bed “flip” times are just the average time a bed sits empty as found in Figure 2-2. For example, when there are 5 or fewer people in the waiting room, the bed “flip” takes 37.6 minutes, when there are 6 to 10 people in the waiting room, the bed “flip” lasts for 22.2 minutes, etc.

2.4 Flexible Capacity

One of the most difficult aspects of the ED to model is the frequent use of hallway beds. Although there are 46 permanent rooms in the ED, there are also extra beds in which patients can be placed and moved into hallway spaces. This increased capacity allows the ED to accommodate over 60 patients on those rare occasions when demand is at its highest. The decision to use hallway spaces when real beds become full, however, is not always automatic. Sometimes patients are placed in hallway beds, but sometimes patients remain in the waiting room until a real bed becomes available.

Our first attempt to model the ED did not include these hallway spaces. After consultation with ED staff and further investigation we realized that our model with a fixed capacity of 46 beds excluded two important phenomena. The first and most obvious omission was that the ED is capable of handling more than 46 patients at a given time due to the practice of placing and administering to patients in temporary hallway spaces, and thus 46 beds would seem to underestimate the true capacity of the ED. However, the predicted waiting times generated by our model with 46 beds seemed relatively accurate and adding even 1 bed caused our model to process patients much faster than was observed in the data. This helped us realize a more subtle omission, which is that often the ED capacity is effectively less than 46 beds.

Figure 2-3 shows the number of patients in the waiting room versus the number of patients occupying beds in the ED. This figure illustrates the fact that often the capacity of the ED is less than the 46 permanent rooms. For example, although the department is capable of treating over 60 patients simultaneously, the average number of patients in the waiting room steadily increases even before there are 40 patients being treated in the ED. Thus, it would appear that some sort of soft limit is being approached before the bed capacity limit is reached. This can be attributed to the fact that a portion of the ED closes during late night hours, and also that in some circumstances it is more desirable to allow a patient to remain in the waiting room for a few minutes rather than placing that patient in a bed immediately. This decision is based on chief complaint, triage level, staff availability, anticipation of future demand,

and/or other factors.

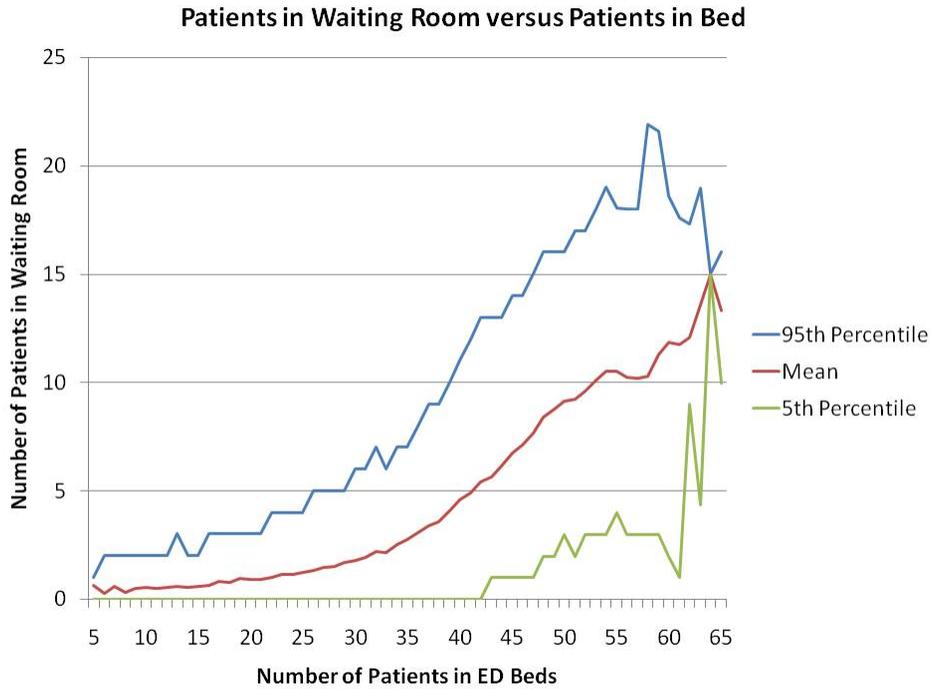


Figure 2-3: Number of Patients in Waiting Room versus Number of Patients in ED.

Figure 2-4 shows the average number of patients being seen in the ED versus the number of patients in the waiting room. Note that as the number of patients waiting increases, the average capacity of the system also increases. With 4 patients in the waiting room, the effective capacity of the ED is approximately 40 patients, while with 12 patients in the waiting room, the effective capacity of the ED is approximately 50 patients. This observation indicates that although the capacity can reach upwards of 60 patients, most of the time it is not desirable to immediately use a hallway space. However, as the length of the waiting room queue grows, the hospital staff is forced to use these hallway spaces to accommodate the growing demand.

We next propose how to model the flexible character of the capacity. In contrast with several other parameters of the model which we were able to estimate explicitly from the data, it was necessary to make an implicit estimate of the parameters for the flexible capacity. We approximated the flexible capacity phenomenon using 4

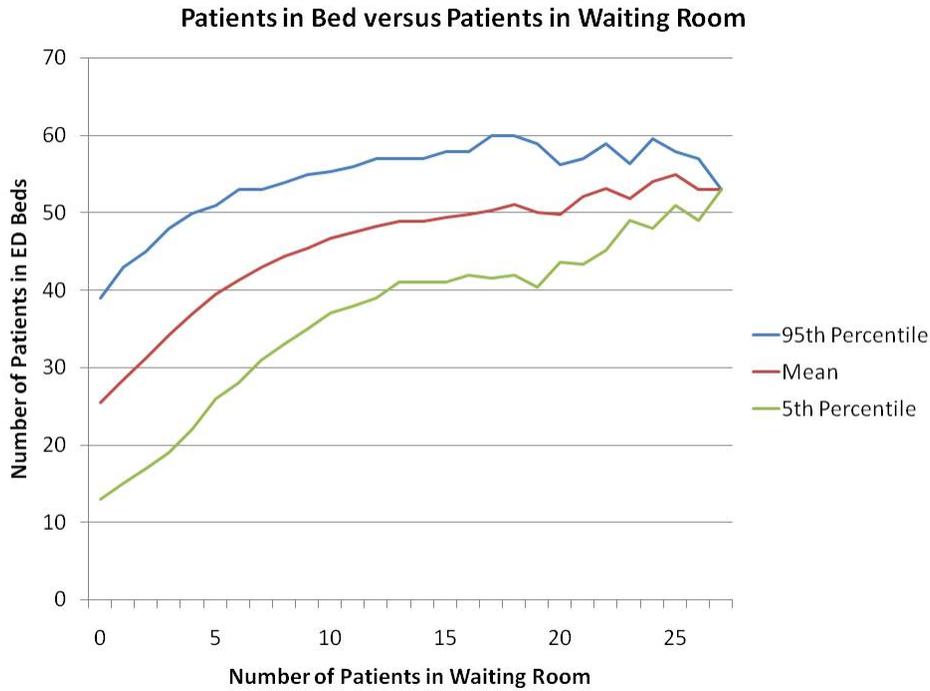


Figure 2-4: Number of Patients in ED versus Number of Patients in Waiting Room.

parameters. These parameters are described in Table 2.7 and depicted graphically in Figure 2-5.

Table 2.7: Flexible Capacity Parameters.

Parameter	Description
α	Length of queue at which capacity starts to increase
β	Length of queue at which capacity reaches maximum
γ	Capacity when queue is empty until queue length is alpha
δ	Capacity when queue length is greater than beta

Although there are many factors that can affect how many beds can be used at any time, including time of day, day of week, number and type of patients already in beds, number and type of patients in the waiting room, and staffing level and ability, we have chosen to model this complex phenomenon using four parameters. We assume there exists a minimum capacity level (denoted γ), the number of beds that are always available for use. This is also the maximum capacity of the system

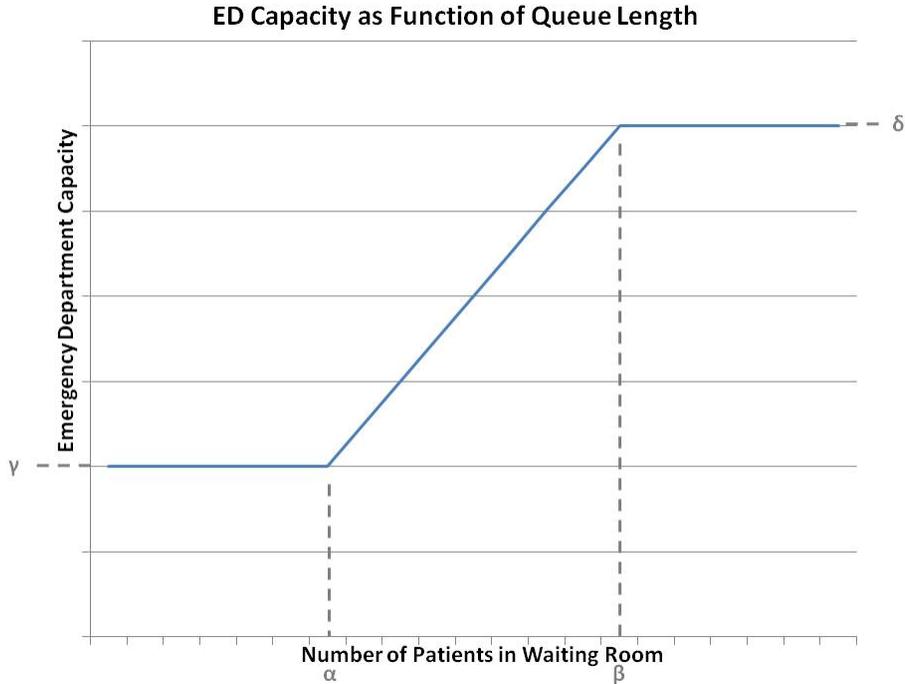


Figure 2-5: ED Capacity as Function of Queue Length.

when the waiting room is empty. We assume there to be a higher capacity level (denoted δ), the maximum number of beds that are ever available for use, even when the number of patients in the waiting room queue is very large. In other words, capacity will never exceed this value. Finally, α is the size of the queue at which capacity begins to increase and β is the size of the queue at which capacity reaches its absolute maximum.

In order to identify the best fit for α , β , γ , and δ , we developed a scoring system to rank how closely the simulation matches the data when using a given set of parameters. This scoring system is based on the predicted and actual mean, standard deviation, and 99th, 95th, 90th, 80th, and 50th percentiles for the waiting time for all ED patients as well as for each of the 5 ESI classes. We ran the simulation with different values for α , β , γ , and δ , and then we used the scoring system to determine which values yielded waiting times for the simulation that most closely matched the data.

To calculate the score for each particular run of the model, we used the sum

of weighted averages of the absolute deviation of waiting time statistics from the simulation to reality (Equation 2.1). The weights are shown in Table 2.8.

$$Score = \sum_{\text{all } i,j} Weight_{ij} \cdot |Simulation_{ij} - Actual_{ij}|$$

where $i = \{Mean, Standard\ Deviation, 99^{th}\ Percentile, 95^{th}\ Percentile, 90^{th}\ Percentile, 80^{th}\ Percentile, 50^{th}\ Percentile\}$

(2.1)

where $j = \{All\ Patients, ESI-1\ Patients, ESI-2\ Patients, ESI-3\ Patients, ESI-4\ Patients, ESI-5\ Patients\}$

Table 2.8: Weights for Absolute Deviation of Waiting Time Statistics Used in Scoring System.

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
Mean	25.0	5.0	5.0	5.0	5.0	5.0
Standard Deviation	15.0	2.0	2.0	2.0	2.0	2.0
99 th Percentile	2.0	1.0	1.0	1.0	1.0	1.0
95 th Percentile	2.0	1.0	1.0	1.0	1.0	1.00
90 th Percentile	2.0	1.0	1.0	1.0	1.0	1.0
80 th Percentile	2.0	1.0	1.0	1.0	1.0	1.0
50 th Percentile	2.0	1.0	1.0	1.0	1.0	1.0

We considered 5,184 models which included various combinations of the four parameters. We tested values of $\alpha \in \{0, \dots, 8\}$ and $\beta \in \{10, \dots, 18\}$. We tested $\gamma \in \{38, \dots, 45\}$ and $\delta \in \{46, \dots, 53\}$.

The model with the best score had a value of 1 for α , 16 for β , 43 for γ , and 47 for δ . The score for this model was 4.758. Scores for the top 10 models are presented in Table 2.9. To perform our analysis and investigate “what-if” scenarios we used the parameters from the best model. It is important to note that the waiting times for all of the models in Table 2.9 were very close to the actual waiting times at BIDMC and any of these models could have been used to investigate the effects of making changes to the ED. The final score of the closest simulation model before including flexible

capacity was 7.901 and the overall average waiting time for the simulation was lower than the actual overall average waiting time by 6.05%. By introducing the concept of flexible capacity we found a model that more closely matches the historical data from BIDMC: the score decreased from 7.9 to 4.8 and the error in the overall average waiting time dropped from 6.05% to 0.28%.

Table 2.9: Flexible Capacity Parameters Yielding Best (Lowest) Scores.

α	β	γ	δ	Score
1	16	43	47	4.758
0	18	43	47	4.785
4	13	43	47	4.831
4	14	43	47	4.845
1	10	43	46	4.850
4	15	43	47	4.865
3	17	43	47	4.886
3	14	43	47	4.936
3	13	43	47	4.944
2	17	43	47	4.956

Chapter 3

Model Validation

We have been careful to ensure that the arrival rates, triage times, waiting room priority, bed times, and bed cleaning times accurately reflect the actual times and processes that occur at BIDMC. Several other criteria have been used to gauge how accurately the simulation model matches the data. These criteria include comparisons of daily arrivals and waiting times.

3.1 Daily Arrivals

The arrival process drives the simulation. In order to accurately model ED operations it is important that the number of patient arrivals in the simulation model each day closely matches the observed number of patient ED arrivals each day at BIDMC from 2/1/05 to 1/31/06. This is especially important considering the increased strain that is placed on ED resources when the arrival rate increases. Although staffing levels can be raised somewhat to meet increased demand there is a fixed amount of space available to observe, diagnose, and treat patients; as the number of arrivals increases, the bottleneck effect on beds becomes more and more pronounced.

Figure 3-1 is a histogram of both the observed number of daily ED arrivals at BIDMC from 2/01/05 to 1/31/06 and the number of daily arrivals in the simulation model. In both cases the number of daily arrivals is between 115 and 140 patients a majority of the time. Having less than 95 or greater than 165 patient arrivals per day

in both cases occurs less than 4% of the time. The arrival process of the simulation model appears to be a reasonable representation of reality.

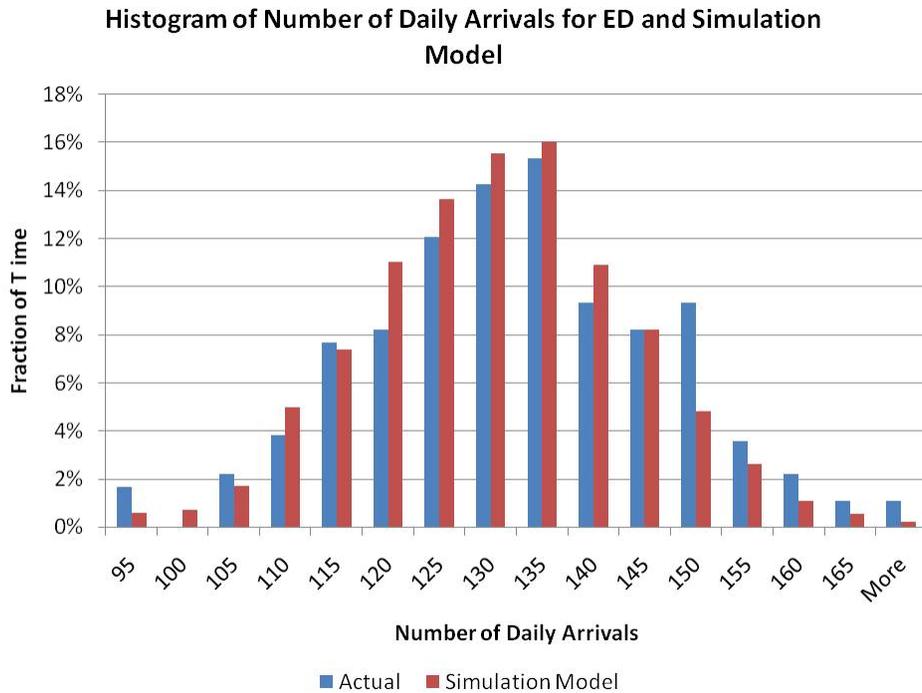


Figure 3-1: Histogram of Number of Actual and Simulation Daily Arrivals.

3.2 Waiting Times

The time patients spend waiting is perhaps the most important indicator of how closely the simulation model matches reality. Several parameters in the model such as the arrival process, triage times, and time patients spend in diagnosis and treatment are explicitly estimated from the data. But the waiting times are dependent on the arrival process, triage times, waiting room priority, bed times, and bed cleaning times and hence the waiting times are an aggregate indicator that the model structure and parameters do not misrepresent the ED dynamics.

Note that because the Dashboard system does not include timestamps for the triage process, the waiting times considered here represent the time from when a patient first presents at the ED until that patient leaves the waiting room and is

assigned a bed. Therefore triage times are included in waiting time for both the historical data (where triage time is implicit) as well as the simulation model (where triage time is explicit).

Table 3.1 and Table 3.2 show the waiting times for patients both historically at BIDMC and in the simulation model. The average waiting time for all patients in the simulation model is only 0.3% higher than the actual average waiting time. The 99th percentiles for both ESI-1 and ESI-2 patients are observed to be larger in reality than predicted by the simulation. This may be due to data errors, such as incorrectly labeled ESI or timestamp errors, or there may be some patients who initially presented with critical symptoms but later stabilized and were able to safely wait until a bed became available.

Table 3.1: Actual Waiting Times (minutes).

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
Mean	41.3	1.5	11.5	50.4	57.3	53.5
Standard Deviation	56.3	7.3	18.3	61.4	58.4	59.9
99 th Percentile	249.0	37.0	90.8	266.0	257.9	269.3
95 th Percentile	163.0	7.9	37.0	183.0	176.3	164.5
90 th Percentile	119.0	1.0	26.0	139.0	137.0	122.0
80 th Percentile	68.0	1.0	17.0	87.0	94.0	86.0
50 th Percentile	18.0	0.0	7.0	25.0	37.0	32.0

Table 3.2: Simulation Waiting Times (minutes).

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
Mean	41.4	1.4	12.8	50.4	56.1	53.7
Standard Deviation	53.8	9.7	14.3	58.1	59.2	56.9
99 th Percentile	245.1	19.4	54.6	260.0	265.8	248.7
95 th Percentile	154.0	7.0	34.9	168.5	178.0	173.7
90 th Percentile	113.3	1.0	30.6	129.1	136.3	132.7
80 th Percentile	69.7	1.0	20.4	86.3	92.3	90.8
50 th Percentile	17.4	0.0	8.4	27.9	32.6	32.2

Chapter 4

“What-if” Analyses

By effectively modeling the patient throughput process in the ED at BIDMC, we are now able to analyze “what-if” scenarios that are important to ED staff and may increase patient throughput. These “what-if” scenarios include adding extra beds, reducing the bed “flip” times, investing in a point of care (POC) troponin test to rapidly diagnose patients with chest pain, and adopting a policy of reserving extra beds for more serious patients (a “nested” bed policy).

4.1 Additional Beds

The ED at BIDMC has identified beds as one of several limiting resources. In this section, we consider the impact of adding extra beds using the simulation model. For the simulation we use the flexible capacity criteria established in Section 2.4 to determine the number of available beds. When we add an extra bed, this represents an upward shift in the entire flexible capacity curve (see Figure 2-5), no matter how large or small the size of the waiting room queue. Results for the additional bed analysis are shown in Table 4.1. The addition of one bed is predicted to result in a 12.1% overall decrease in average waiting time, from 41.4 minutes to 36.4 minutes. Also, reducing the amount of available beds by one a 14.8% overall increase in average waiting time. Adding up to 4 additional beds would lead to a 37.1% overall decrease in average waiting time. More extensive results including the predicted mean, stan-

dard deviation, and percentiles of waiting times for each ESI level are contained in Appendix A.1. For each of the scenarios, one bed is held in reserve for ESI-1 patients, and bed “flip” times are those specified in the baseline model presented in Figure 2-2.

Table 4.1: Percent Change in Average Waiting Time from Baseline Bed Scenario.

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
-1 Bed	14.8%	18.1%	5.9%	15.8%	14.3%	15.4%
Current	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
+1 Bed	-12.1%	-12.7%	-5.1%	-12.9%	-11.7%	-11.8%
+2 Beds	-22.1%	-23.8%	-9.4%	-23.5%	-21.3%	-22.0%
+3 Beds	-30.3%	-33.0%	-13.2%	-32.3%	-29.2%	-30.4%
+4 Beds	-37.1%	-39.9%	-16.8%	-39.4%	-35.7%	-36.9%

Note that we consider only small perturbations to existing conditions when proposing policy changes. Undoubtedly adding many extra beds would require extra physicians, nurses, technicians, and equipment to be able to assume the same service times and thus predictions by this model for making large changes should be viewed with less confidence. However, for small changes it is not unreasonable to believe that service times will remain relatively constant.

4.2 Bed “Flip” Times

The time required for cleaning and reassigning beds is not readily available from the data. However, there is evidence to suggest that several minutes are required from when a patient leaves a bed until that bed is ready for the next patient to enter. The “what-if” analysis in this section investigates the effect that reducing bed “flip” times could have on patient waiting times. We consider reducing the bed “flip” times by up to 25 minutes, although for each of the scenarios the bed “flip” times are not reduced below 10.7 minutes which was found to be the fastest average bed “flip” time when the waiting room is full (see Figure 2-2). Complete results for the analysis are available in Table 4.2. A reduction of 5 minutes in the bed “flip” time is predicted

to result in a 6.2% overall decrease in average patient waiting time, and a bed “flip” time reduction of 10 minutes an 11.3% decrease in average patient waiting time. More extensive results for the bed “flip” analysis including the predicted mean, standard deviation, and percentiles of waiting times overall and for each ESI level are contained in Appendix A.2.

Table 4.2: Percent Change in Average Waiting Time from Baseline Bed “Flip” Scenario.

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
+5 min	7.2%	8.7%	3.0%	7.6%	7.0%	7.5%
Current	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
-5 min	-6.2%	-6.2%	-2.7%	-6.6%	-5.9%	-6.3%
-10 min	-11.3%	-11.5%	-5.2%	-12.0%	-10.8%	-11.3%
-15 min	-14.9%	-14.5%	-7.3%	-15.8%	-14.3%	-14.8%
-20 min	-18.0%	-17.5%	-9.1%	-19.0%	-17.2%	-17.9%
-25 min	-20.9%	-19.0%	-10.8%	-22.1%	-20.0%	-20.7%

4.3 Point of Care Troponin Test

The physicians at BIDMC ED are considering a POC troponin test as a possible way to increase throughput at BIDMC. This device would substantially reduce the amount of time required to identify the troponin levels in patients with chest pain. When troponin levels are sufficiently elevated it is a strong indication of cardiac muscle damage. Of the 47,537 patients who presented to BIDMC ED from 2/1/05 to 1/31/06, 3185 patients had chest pain as a chief complaint. A smaller subset of 2632 patients had chest pain as a chief complaint *and* a troponin lab test.

There are several factors that affect the final disposition (i.e., discharge versus admit) of patients in the ED. Physicians at BIDMC estimate that using a POC troponin test could reduce the time required to determine the disposition of a chest pain patient by at least 20 minutes up to 1 hour. Thus, to analyze the benefit of the proposed POC troponin test, we reduce the simulated bed times for those patients

on whom the troponin device would be used.

In order to simulate the arrival of patients with chest pain to the ED, a certain fraction (Table 4.3) of each type of patient (ESI 1-5) was randomly assigned to be a chest pain patient. For this fraction of patients, the time in bed is reduced to simulate the effect the POC troponin test could have.

Table 4.3: Percentage of Patients Presenting with Chest Pain.

ESI Level	Total Patients	Chest Pain Patients	% of ESI Level
All Patients	47537	3185	6.7%
ESI-1	1165	7	0.6%
ESI-2	10910	2003	18.4%
ESI-3	28372	1148	4.1%
ESI-4	6756	25	0.4%
ESI-5	332	2	0.6%

Table 4.4 shows the predicted effects of reducing the time required to determine the disposition of chest pain patients. If ED physicians were able reduce the time necessary to determine the disposition of troponin patients by 60 minutes using the troponin test, average patient waiting time (for all patients, not just chest pain patients) is predicted to decrease by 5.3%. Note that reducing the diagnosis and treatment time of a subset of patients reduces the average waiting time for all patients. It is also important to note that the critical factor here is not how long it takes to determine the troponin levels, but how long it takes to determine the disposition of the patient. Certainly reducing the time to determine the troponin levels will help reduce the time to determine disposition but other factors may affect this time as well. More extensive results for the POC troponin analysis including the predicted mean, standard deviation, and percentiles of waiting times overall and for each ESI level are contained in Appendix A.3.

Table 4.4: Percent Change in Average Waiting Time from Baseline Chest Pain Diagnosis Scenario.

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
+20 min	1.9%	2.2%	0.8%	2.0%	1.8%	2.1%
Current	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
-20 min	-1.9%	-1.2%	-0.8%	-2.0%	-1.8%	-1.8%
-40 min	-3.7%	-2.0%	-1.5%	-4.0%	-3.6%	-3.7%
-60 min	-5.3%	-4.1%	-2.1%	-5.7%	-5.1%	-5.1%

4.4 “Nested” Beds

The “nested” bed policy is based on the idea of reserving a certain number of beds for patients of given acuity levels. This idea was motivated by the use of nested fare classes in airlines as a way to maximize profit [6]. The current policy at BIDMC is to reserve one bed for trauma patients who arrive via ambulance, most of whom are ESI-1. These patients can occupy any bed in the ED if available, but no other patients can occupy this one reserved bed. The “what-if” analysis in this section extends that idea to both ESI-1 and ESI-2 patients, and to multiple beds. For the following scenarios denoted “**A-B**”, **A** refers to the number of beds that are available exclusively for ESI-1 patients and **B** refers to the number of beds that are available for either ESI-1 or ESI-2 patients. To further clarify this policy, ESI-1 patients can occupy any of the beds in the ED, ESI-2 patients can occupy any of the beds in the ED except for the **A** beds, and ESI-3, 4, and 5 patients can occupy any of the beds in the ED except for the **A** and **B** beds.

Results of the analysis are summarized in Table 4.5. Note that changing from the current **1-0** policy to a **1-2** policy is predicted to increase overall average waiting time by 0.2%, and average waiting time for ESI-3, ESI-4, and ESI-5 patients by 0.4%, but could reduce ESI-2 average waiting time by 2.5% and reduce ESI-1 average waiting time by 0.3%. More extensive results for the “nested” bed analysis including the predicted mean, standard deviation, and percentiles of waiting times overall and for each ESI level are contained in Appendix A.4.

Table 4.5: Percent Change in Average Waiting Time from Baseline **1-0** “Nested” Bed Policy.

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
0-0	-1.0%	11.3%	-0.8%	-1.0%	-0.9%	-1.1%
0-1	-1.0%	10.4%	-2.0%	-0.9%	-0.9%	-1.0%
0-2	-1.0%	10.4%	-3.2%	-0.8%	-0.7%	-0.9%
0-3	-0.9%	8.3%	-4.4%	-0.7%	-0.6%	-0.8%
0-4	-0.8%	8.5%	-5.7%	-0.5%	-0.4%	-0.6%
1-0*	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
1-1	0.1%	-0.1%	-1.3%	0.2%	0.2%	0.1%
1-2	0.2%	-0.3%	-2.5%	0.4%	0.4%	0.4%
1-3	0.4%	-0.1%	-3.8%	0.7%	0.7%	0.7%
1-4	0.7%	-0.5%	-5.1%	1.1%	1.1%	1.1%
2-0	2.6%	-5.2%	2.3%	2.7%	2.5%	2.7%
2-1	2.9%	-4.5%	0.9%	3.1%	2.9%	3.2%
2-2	3.2%	-4.5%	-0.5%	3.5%	3.3%	3.8%
2-3	3.7%	-3.9%	-1.9%	4.2%	3.8%	4.4%
2-4	4.3%	-3.5%	-3.2%	5.0%	4.5%	5.1%

*Current Scenario

4.5 Combined Effects

In Sections 4.1 through 4.4, we have evaluated four separate policies in isolation to estimate the respective isolated effect of implementing each policy. Another option is to consider changing several policies simultaneously and estimating the overall effect. For example, the ED staff could invest in a POC troponin device and create an extra bed for patients to occupy. Table 4.6 shows the net effect that changing several policies could have. Each policy change considered in Table 4.6 is in addition to policy changes already made, thus, the first row shows predicted effects of adding an extra bed, the second row shows the predicted effects of adding an extra bed *and* reducing the bed “flip” time, etc. These changes were also added in descending order of impact (adding an extra bed had the greatest impact, followed by reducing the bed “flip” times). If the ED staff added an extra bed, reduced the bed cleaning time by 5 minutes, invested in the POC troponin device, and reserved an additional bed for ESI-1 and ESI-2 patients (a **1-1** nested bed policy), the average waiting time of each patient is predicted to decrease by 21.4%. More extensive results for the analysis of these combined effects including the predicted mean, standard deviation, and percentiles of waiting times overall and for each ESI level are contained in Appendix A.5.

Table 4.6: Percent Change in Average Waiting Time from Baseline Scenario.

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
+ Extra Bed	-12.1%	-12.7%	-5.1%	-12.9%	-11.7%	-11.8%
- 5 min Bed “Flip”	-17.3%	-18.1%	-7.4%	-18.5%	-16.8%	-16.8%
- 60 min Troponin	-21.4%	-21.4%	-9.1%	-22.8%	-20.6%	-20.9%
+ 1,1 Nested Policy	-21.4%	-22.0%	-10.0%	-22.7%	-20.5%	-20.9%

*Each row indicates changes made in addition to those of previous rows.

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Chapter 5

Further Extensions

In addition to the policy changes already considered here, several other “what-if” scenarios have been proposed and should be considered for future evaluation using the simulation model. One such scenario involves determining the effectiveness of adding a “Fast-Track” zone to the ED which exclusively administers to less acute patients. Several hospitals have adopted this policy in order to reduce waiting time for patients who generally have shorter lengths of stay. Nash et al. [18] found that utilizing a fast-track area did lead to reduced overall waiting times. This policy presumes to create space and reduce the number of people in the waiting room when the ED becomes congested. BIDMC has tried this policy several times but for various reasons the policy has never become permanent. By quantifying the predicted reduction in waiting times by adding a “fast-track” zone, it may be possible to determine the “level of indifference” in the BIDMC ED for reduced waiting times.

BIDMC ED has already taken steps to implement some of the proposals in this thesis, including adding an additional bed (by splitting one large room into two smaller rooms) and reducing the bed “flip” times. Further work in this area could include observing the new data after the proposed changes have taken effect to evaluate their impact.

Another proposal for future evaluation is to identify key groups of patients who cause significant delays to the system as a whole. For example, such groups might include MRI patients or psychiatric patients. Identifying such groups and quantifying

their above-average utilization of ED resources may provide motivation to discover solutions and make improvements in the way ED personnel administer treatment to these groups. BIDMC personnel have suggested that competition for imaging equipment is a significant factor in lower patient throughput [10]. Green et al. [12] have formulated the scheduling of competing radiology equipment as a dynamic-programming problem. Such analyses could be extended to the BIDMC ED.

For the purposes of this thesis we have considered the reduction of patient waiting time as the key indicator of improved patient throughput and the chief desirable outcome. We have not considered the specific revenue implications of the policies and changes we have proposed and analyzed. It has been shown that hospital accounting departments generally underestimate the cost of outpatient visits to the ED [3]. Future research could seek to quantify and predict the financial impact that the policy changes might cause. For example, a study could be used to determine whether the financial benefits gained by increasing patient throughput using the POC troponin test would be worth the cost of purchasing the tests, or whether revenue implications justify additional resources to increase bed capacity or reduce bed “flip” times.

A topic of significant interest to ED personnel is to identify the effect that external factors have on ED waiting times. In this thesis we have only considered internal solutions local to the ED to increase the patient throughput. There are many external factors that cause delays within the ED, such as over-scheduling hospital inpatient beds and limiting resources such as imaging equipment and hospital-wide lab facilities. Unfortunately, these “external” causes of delay are harder to alleviate. While ED personnel at BIDMC have significant power to make changes to policies within the ED, it is a much larger challenge to influence hospital-wide policies and priorities. For this reason it would be beneficial to quantify hospital-wide impacts of improved ED operations. It is hoped that such evidence could help influence hospital management to better evaluate the impacts of proposed improvements. Beliën et al. [4] have developed a software system that shows the impact that the master surgery schedule has on the rest of the hospital. It would be of interest to investigate the master surgery schedule at BIDMC and investigate how changes might affect the availability

of inpatient beds for ED patients waiting to be admitted.

One of the most significant external factors affecting patient throughput in the ED at BIDMC is the number of inpatient beds that are available in the hospital. Bagust et al. [2] investigate the effect that inpatient capacity has on an emergency department and seek to quantify the risks of having insufficient capacity. When inpatient bed availability is high, patients admitted to the hospital from the ED occupy ED beds for a much shorter period of time. Conversely, when inpatient bed availability is low, admitted patients can spend on average up to three *extra* hours waiting for a bed to become available.

For each patient who is admitted to the hospital from the ED, there are two components which constitute the time that patient occupies an ED bed. First, there is an initial period when the patient is still being diagnosed and evaluated. Nurses and physicians observe the patient, order lab tests and radiology exams, and gather information about the patient's condition until the physician is able to make a determination about whether the patient should be admitted to the hospital or not. It takes approximately 3.5 hours on average to make the decision to admit the patient.

Once the decision has been made that the patient should be admitted, coordination begins to take place between ED staff and other hospital departments to determine which department of the hospital the patient should be admitted to, whether or not there is a bed available for the patient in that department, and what equipment will be needed to facilitate the transfer. ED physicians and nurses will continue to oversee the condition of patients for whom a bed has been requested until that patient is moved to the hospital, but most of the active diagnostic work is done by ED staff before the bed is requested.

It is this second component of the time in bed that is seriously affected by the availability of inpatient beds. The hospital occupancy is defined as the percentage of inpatient hospital beds that are full at a given time. When hospital occupancy is less than 78.9% (approximately one-fourth of the time), patients wait 5.1 hours on average to be admitted to the hospital once a bed has been requested. On the other extreme, when hospital occupancy is greater than 86.5% (approximately one-fourth

of the time), patients wait 8.0 hours on average to be admitted to the hospital once a bed has been requested.

Figure 5-1 shows the average diagnosis time and average time waiting to be admitted for patients admitted from the ED to the hospital. The sum of these two numbers is the total time a patient spends in an ED bed. The diagnosis time is measured from when the patient enters the bed until a hospital inpatient bed is requested for that patient. The time waiting to be admitted is measured from when the hospital inpatient bed has been requested until the patient leaves the ED. The diagnosis time appears to be unaffected by the hospital occupancy level, meaning that regardless of how many inpatient beds are available, it takes the same amount of time on average for physicians at the BIDMC ED to make the decision to admit a patient. The average admission wait time, on the other hand, rises steadily as hospital occupancy increases. This represents the time from when an inpatient bed is first requested for an ED patient until that patient leaves the ED.

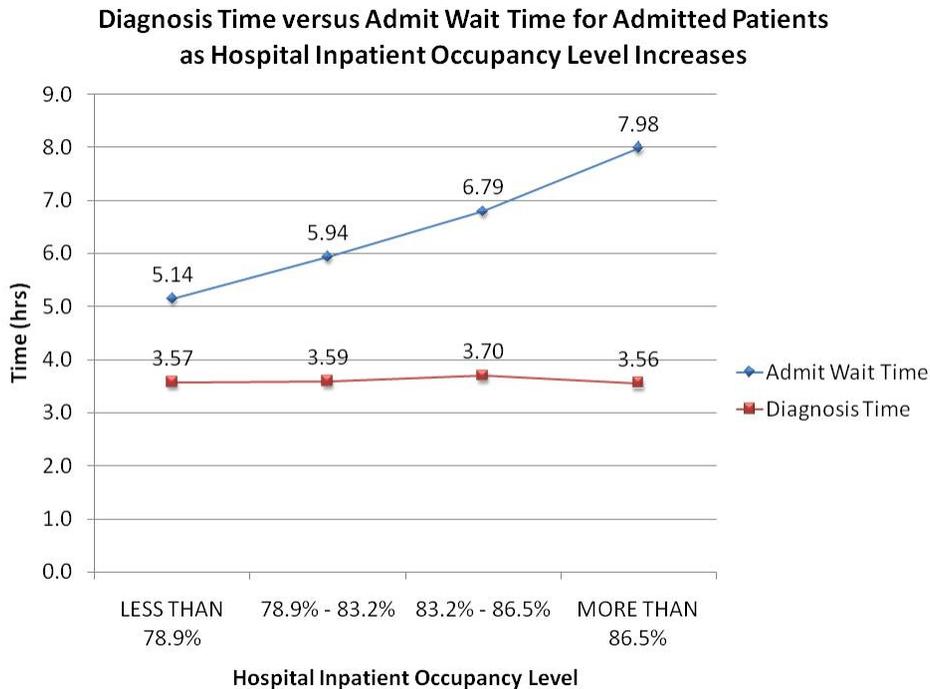


Figure 5-1: Effects of Inpatient Bed Availability on Admitted ED Patients.

Figure 5-2 shows the average time in bed for admitted patients and discharged

patients as a function of hospital inpatient capacity. This figure also helps illustrate the bottleneck effect that occurs as the number of available inpatient beds decreases. The time in bed for patients who are discharged from the ED to go home appears unaffected by inpatient capacity (as one would expect), but the time in bed for admitted patients rises steadily as the number of occupied hospital beds increases. These admitted patients spend several hours occupying ED beds, a limiting resource on ED operations, when they should be admitted to the hospital. This can prevent other waiting patients from being seen by ED doctors.

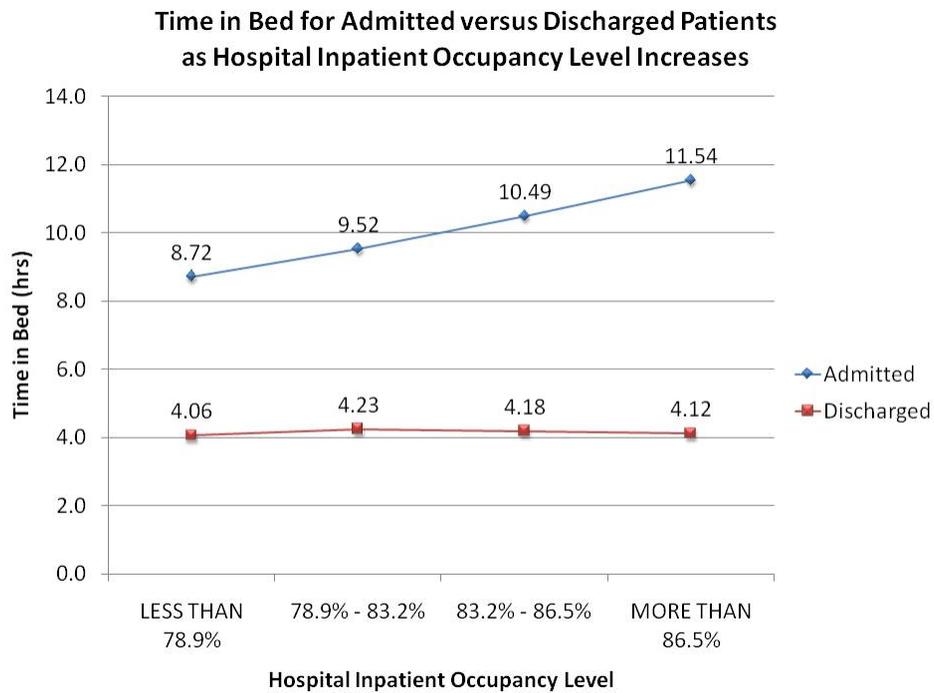


Figure 5-2: Effects of Inpatient Bed Availability on All ED Patients.

Further analysis might be extended to quantify the effect of increasing hospital inpatient capacity or reserving extra space for ED patients. Garson et al. [11] have found that patients would prefer to be boarded in inpatient hallway spaces rather than ED hallway spaces. It is worth investigating whether the revenue implications of increasing ED throughput would justify reserving or increasing inpatient bed capacity.

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Chapter 6

Conclusions

The Dashboard data collected and provided by BIDMC and the active assistance and support by the ED staff, has allowed for extensive and accurate modeling of ED operations. We have modeled patient arrivals using linear regression based on time of day, day of the week, and previous arrivals with a resulting R^2 value of 0.84. We have modeled patient “flow” using discrete event simulation. We have calibrated simulation parameters to match historical data provided by the BIDMC Dashboard system from 2/1/05 to 1/31/06. Parameters include the arrival rates, triage times, waiting room priority, bed assignment policy, number of beds available, patient bed times, and bed cleaning times. Several indicators help validate the accuracy of the simulation model when compared with the actual data including histograms of the number of daily arrivals and the waiting times.

With this understanding of the arrival and “flow” of ED patients, we were equipped to analyze several “what if” scenarios. The first such analysis quantified the impact on patient waiting times of adding extra bed capacity to the ED. The addition of one extra bed led to an estimated reduction in average patient waiting time of 12.1%. Another “what-if” scenario estimated the effect of reducing the time required to “flip” beds. Reducing this time by 5 minutes led to an estimated reduction in waiting time of approximately 6% for the average patient, while reducing the bed “flip” time by 10 minutes led to an estimated reduction in average waiting time of 11%. A third analysis estimated that reducing the time required to diagnose chest pain patients by

60 minutes using a point of care troponin device would lead to a reduction in average patient waiting time of 5.3%. A final proposal estimated the impact of reserving additional beds for patients arriving with more severe conditions. A **1-2** nested bed policy was predicted to reduce waiting time for ESI-1 and ESI-2 patients by approximately 0.3% and 2.5%, respectively.

In addition to estimating the effects of implementing the proposed policies in isolation, we also analyzed the effects of implementing several of them simultaneously. Adding one bed, reducing the bed “flip” time by 5 minutes, using a POC troponin device to reduce the time necessary to determine the disposition of chest pain patients by 1 hour, and reserving an extra bed for ESI-1 and ESI-2 patients would result in an estimated reduction in average waiting time of 21.4% per patient.

This modeling effort is novel in several ways. It relies on a relatively sophisticated arrival module that includes a learning effect. The model is responsive to the state of the system by including flexible capacity and faster service times as workload increases. Most importantly, because the predicted waiting times generated by the model closely match those observed in the data, the model can be used to evaluate the impact of proposed policy changes. Future research should include investigating the impact that hospital-wide policies have on the waiting times of ED patients and quantifying the financial impact of proposed policy changes in the ED.

Appendix A

“What-If” Analyses Results

A.1 Additional Bed Analysis

Baseline Bed Scenario -1 Bed.

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
Mean	47.5	1.7	13.5	58.4	64.1	61.9
Standard Deviation	60.9	11.4	15.6	65.4	66.5	64.6
99 th Percentile	274.9	26.7	57.8	291.0	296.8	272.7
95 th Percentile	174.7	7.6	36.8	190.7	199.7	195.9
90 th Percentile	130.7	1.0	30.6	147.6	155.6	155.0
80 th Percentile	81.6	1.0	21.9	101.8	108.1	106.4
50 th Percentile	22.2	0.0	8.7	31.2	40.8	37.2

Baseline Bed Scenario.

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
Mean	41.4	1.4	12.8	50.4	56.1	53.7
Standard Deviation	53.8	9.7	14.3	58.1	59.2	56.9
99 th Percentile	245.1	19.4	54.6	260.0	265.8	248.7
95 th Percentile	154.0	7.0	34.9	168.5	178.0	173.7
90 th Percentile	113.3	1.0	30.6	129.1	136.3	132.7
80 th Percentile	69.7	1.0	20.4	86.3	92.3	90.8
50 th Percentile	17.4	0.0	8.4	27.9	32.6	32.2

Baseline Bed Scenario +1 Bed.

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
Mean	36.4	1.3	12.1	43.9	49.5	47.4
Standard Deviation	47.7	8.4	13.4	51.7	52.8	50.4
99 th Percentile	219.8	15.2	51.3	234.0	240.8	223.6
95 th Percentile	135.9	6.0	33.5	149.3	157.5	155.5
90 th Percentile	98.3	1.0	30.6	112.9	120.6	117.0
80 th Percentile	64.8	1.0	18.8	72.2	78.1	77.4
50 th Percentile	16.8	0.0	8.4	22.2	29.4	26.4

Baseline Bed Scenario +2 Beds.

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
Mean	32.3	1.1	11.6	38.5	44.2	41.8
Standard Deviation	42.5	7.4	12.5	46.1	47.4	44.5
99 th Percentile	197.3	12.0	48.8	210.7	217.2	195.4
95 th Percentile	120.3	5.5	31.6	132.5	141.3	136.5
90 th Percentile	84.5	1.0	30.6	98.6	106.1	101.3
80 th Percentile	58.5	1.0	17.2	64.8	77.4	64.6
50 th Percentile	16.2	0.0	8.4	22.2	28.0	26.4

Baseline Bed Scenario +3 Beds.

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
Mean	28.8	1.0	11.1	34.1	39.7	37.3
Standard Deviation	37.9	6.4	11.9	41.1	42.6	39.5
99 th Percentile	178.2	12.0	46.1	189.4	196.9	178.2
95 th Percentile	106.2	3.0	30.6	117.6	125.5	120.0
90 th Percentile	76.9	1.0	30.6	85.2	92.5	89.6
80 th Percentile	47.2	1.0	16.2	64.8	77.4	55.2
50 th Percentile	13.8	0.0	7.7	16.8	22.2	21.0

Baseline Bed Scenario +4 Beds.

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
Mean	26.0	0.9	10.6	30.5	36.1	33.9
Standard Deviation	34.0	5.6	11.3	36.9	38.5	35.5
99 th Percentile	161.0	12.0	43.7	171.6	179.8	166.2
95 th Percentile	93.3	3.0	30.6	104.4	112.3	107.9
90 th Percentile	64.8	1.0	30.6	72.5	79.4	77.7
80 th Percentile	40.8	1.0	16.2	60.2	65.6	55.2
50 th Percentile	12.6	0.0	6.6	16.8	22.2	21.0

A.2 Bed “Flip” Analysis

Baseline Bed “Flip” Scenario +5 Minutes.

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
Mean	44.4	1.6	13.1	54.2	60.0	57.7
Standard Deviation	57.2	10.4	15.0	61.7	62.8	60.6
99 th Percentile	259.5	22.0	56.5	275.0	280.2	261.8
95 th Percentile	164.2	7.1	36.0	179.4	188.8	184.3
90 th Percentile	121.9	1.0	30.6	138.5	145.8	142.3
80 th Percentile	76.9	1.0	21.2	94.0	100.2	99.5
50 th Percentile	20.4	0.0	8.4	31.2	40.4	37.2

Baseline Bed “Flip” Scenario.

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
Mean	41.4	1.4	12.8	50.4	56.1	53.7
Standard Deviation	53.8	9.7	14.3	58.1	59.2	56.9
99 th Percentile	245.1	19.4	54.6	260.0	265.8	248.7
95 th Percentile	154.0	7.0	34.9	168.5	178.0	173.7
90 th Percentile	113.3	1.0	30.6	129.1	136.3	132.7
80 th Percentile	69.7	1.0	20.4	86.3	92.3	90.8
50 th Percentile	17.4	0.0	8.4	27.9	32.6	32.2

Baseline Bed “Flip” Scenario -5 Minutes.

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
Mean	38.8	1.4	12.4	47.1	52.8	50.3
Standard Deviation	51.0	9.1	13.8	55.2	56.4	53.7
99 th Percentile	235.0	15.3	52.6	250.9	256.5	236.3
95 th Percentile	144.5	7.0	33.9	159.1	167.9	160.7
90 th Percentile	105.4	1.0	30.6	120.6	128.0	122.9
80 th Percentile	64.8	1.0	19.6	79.0	85.1	84.6
50 th Percentile	16.8	0.0	8.4	22.2	29.4	26.4

Baseline Bed “Flip” Scenario -10 Minutes.

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
Mean	36.7	1.3	12.1	44.3	50.0	47.6
Standard Deviation	49.0	8.7	13.4	53.2	54.4	51.6
99 th Percentile	229.6	14.1	51.0	245.4	252.6	230.1
95 th Percentile	137.5	6.0	33.1	151.6	160.8	156.2
90 th Percentile	98.3	1.0	30.6	113.6	120.9	117.3
80 th Percentile	64.8	1.0	18.7	72.1	78.0	77.6
50 th Percentile	16.8	0.0	8.4	22.2	29.4	26.4

Baseline Bed “Flip” Scenario -20 Minutes.

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
Mean	35.2	1.2	11.8	42.4	48.1	45.7
Standard Deviation	47.9	8.5	13.2	52.1	53.4	50.5
99 th Percentile	227.0	13.0	49.8	242.6	249.2	226.1
95 th Percentile	133.7	6.0	32.3	148.3	157.0	152.3
90 th Percentile	93.7	1.0	30.6	109.2	117.1	112.3
80 th Percentile	64.8	1.0	17.9	67.0	77.4	72.8
50 th Percentile	16.8	0.0	8.4	22.2	29.4	26.4

Baseline Bed “Flip” Scenario -25 Minutes.

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
Mean	34.0	1.2	11.6	40.8	46.5	44.0
Standard Deviation	47.1	8.2	13.0	51.3	52.6	49.8
99 th Percentile	225.0	12.0	49.0	240.5	247.1	225.0
95 th Percentile	130.9	6.0	31.6	145.8	154.4	149.3
90 th Percentile	89.7	1.0	30.6	105.9	113.7	108.3
80 th Percentile	61.4	1.0	17.1	64.8	77.4	67.7
50 th Percentile	16.2	0.0	8.4	22.2	28.2	26.4

Baseline Bed “Flip” Scenario -30 Minutes.

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
Mean	32.8	1.2	11.4	39.3	44.9	42.5
Standard Deviation	46.3	8.1	12.8	50.6	51.8	48.9
99 th Percentile	223.0	12.0	48.3	238.7	245.5	221.0
95 th Percentile	127.8	6.0	30.9	143.2	151.3	148.1
90 th Percentile	85.4	1.0	30.6	102.1	109.7	105.3
80 th Percentile	56.2	1.0	16.5	64.8	77.4	62.1
50 th Percentile	16.0	0.0	8.4	16.8	22.2	24.5

A.3 POC Troponin Test Analysis

Baseline Chest Pain Diagnosis Scenario +20 Minutes.

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
Mean	42.2	1.5	12.9	51.4	57.1	54.7
Standard Deviation	54.7	9.8	14.5	59.0	60.2	58.0
99 th Percentile	249.1	19.9	55.1	265.0	271.2	254.1
95 th Percentile	156.7	7.0	35.2	171.5	180.5	176.8
90 th Percentile	115.7	1.0	30.6	131.6	139.0	134.9
80 th Percentile	71.6	1.0	20.7	88.2	94.3	92.5
50 th Percentile	17.9	0.0	8.4	29.8	34.7	35.1

Baseline Chest Pain Diagnosis Scenario.

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
Mean	41.4	1.4	12.8	50.4	56.1	53.7
Standard Deviation	53.8	9.7	14.3	58.1	59.2	56.9
99 th Percentile	245.1	19.4	54.6	260.0	265.8	248.7
95 th Percentile	154.0	7.0	34.9	168.5	178.0	173.7
90 th Percentile	113.3	1.0	30.6	129.1	136.3	132.7
80 th Percentile	69.7	1.0	20.4	86.3	92.3	90.8
50 th Percentile	17.4	0.0	8.4	27.9	32.6	32.2

Baseline Chest Pain Diagnosis Scenario -20 Minutes.

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
Mean	40.6	1.4	12.7	49.4	55.1	52.7
Standard Deviation	52.8	9.5	14.2	57.1	58.2	55.7
99 th Percentile	240.7	18.9	54.2	256.0	262.2	242.2
95 th Percentile	151.0	7.0	34.6	165.4	174.1	169.5
90 th Percentile	111.0	1.0	30.6	126.6	133.3	130.4
80 th Percentile	67.8	1.0	20.2	84.3	90.4	89.6
50 th Percentile	17.4	0.0	8.4	25.8	30.5	30.2

Baseline Chest Pain Diagnosis Scenario -40 Minutes.

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
Mean	39.9	1.4	12.6	48.4	54.1	51.7
Standard Deviation	51.9	9.4	14.0	56.1	57.3	54.6
99 th Percentile	236.8	19.4	53.7	251.3	258.0	233.1
95 th Percentile	148.3	7.0	34.5	162.5	171.8	167.8
90 th Percentile	108.8	1.0	30.6	124.1	131.1	127.2
80 th Percentile	66.0	1.0	20.0	82.2	88.1	87.3
50 th Percentile	16.9	0.0	8.4	23.5	29.4	27.7

Baseline Chest Pain Diagnosis Scenario -60 Minutes.

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
Mean	39.2	1.4	12.5	47.5	53.2	50.9
Standard Deviation	51.0	9.2	13.9	55.2	56.4	53.7
99 th Percentile	233.5	18.5	53.4	247.7	253.4	229.8
95 th Percentile	145.9	7.0	34.3	159.7	168.9	163.3
90 th Percentile	106.7	1.0	30.6	122.0	129.1	125.4
80 th Percentile	64.8	1.0	19.8	80.4	86.3	85.9
50 th Percentile	16.8	0.0	8.4	22.2	29.4	26.4

A.4 “Nested” Bed Policy Analysis

0-0 “Nested” Bed Policy.

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
Mean	41.0	1.6	12.7	49.9	55.6	53.1
Standard Deviation	52.7	9.6	14.1	56.8	58.0	55.5
99 th Percentile	237.5	23.5	54.4	251.5	257.6	237.9
95 th Percentile	151.8	10.0	34.6	165.5	174.4	168.1
90 th Percentile	112.6	1.0	30.6	127.8	134.9	131.7
80 th Percentile	69.5	1.0	20.1	85.9	91.9	90.5
50 th Percentile	17.4	0.0	8.4	27.6	32.3	32.1

0-1 “Nested” Bed Policy.

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
Mean	41.0	1.6	12.5	49.9	55.6	53.1
Standard Deviation	52.8	9.6	14.1	56.9	58.2	55.6
99 th Percentile	238.5	22.8	54.0	252.6	258.7	237.9
95 th Percentile	151.9	10.0	34.3	165.8	174.8	167.7
90 th Percentile	112.7	1.0	30.6	127.9	135.0	131.7
80 th Percentile	69.5	1.0	19.7	85.9	91.9	90.5
50 th Percentile	17.4	0.0	8.4	27.6	32.3	32.1

0-2 “Nested” Bed Policy.

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
Mean	41.0	1.6	12.3	50.0	55.7	53.2
Standard Deviation	53.0	9.6	14.1	57.1	58.3	55.7
99 th Percentile	239.4	22.8	53.8	253.5	260.1	238.3
95 th Percentile	152.2	9.7	33.7	166.2	175.2	169.0
90 th Percentile	112.8	1.0	30.6	128.1	135.2	132.3
80 th Percentile	69.5	1.0	19.3	86.0	92.0	90.3
50 th Percentile	17.4	0.0	8.4	27.6	32.3	32.3

0-3 “Nested” Bed Policy.

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
Mean	41.0	1.6	12.2	50.0	55.7	53.2
Standard Deviation	53.1	9.7	14.0	57.3	58.5	55.9
99 th Percentile	240.3	21.3	53.5	255.0	261.8	238.9
95 th Percentile	152.6	8.9	33.3	166.6	175.5	169.0
90 th Percentile	112.9	1.0	30.6	128.2	135.3	132.5
80 th Percentile	69.6	1.0	18.8	86.0	92.0	91.0
50 th Percentile	17.4	0.0	8.4	27.6	32.3	32.3

0-4 “Nested” Bed Policy.

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
Mean	41.1	1.6	12.0	50.1	55.8	53.3
Standard Deviation	53.3	9.7	14.0	57.5	58.7	56.1
99 th Percentile	241.7	21.3	53.2	256.2	262.4	238.9
95 th Percentile	153.1	8.9	32.8	167.2	176.2	171.6
90 th Percentile	113.1	1.0	30.6	128.5	135.6	132.0
80 th Percentile	69.6	1.0	18.3	86.1	92.3	91.0
50 th Percentile	17.3	0.0	8.4	27.6	32.4	33.0

1-0 “Nested” Bed Policy (Current Scenario).

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
Mean	41.4	1.4	12.8	50.4	56.1	53.7
Standard Deviation	53.8	9.7	14.3	58.1	59.2	56.9
99 th Percentile	245.1	19.4	54.6	260.0	265.8	248.7
95 th Percentile	154.0	7.0	34.9	168.5	178.0	173.7
90 th Percentile	113.3	1.0	30.6	129.1	136.3	132.7
80 th Percentile	69.7	1.0	20.4	86.3	92.3	90.8
50 th Percentile	17.4	0.0	8.4	27.9	32.6	32.2

1-1 “Nested” Bed Policy.

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
Mean	41.4	1.4	12.6	50.5	56.2	53.7
Standard Deviation	54.0	9.7	14.3	58.3	59.5	57.1
99 th Percentile	246.3	19.1	54.2	261.6	266.6	254.1
95 th Percentile	154.4	7.0	34.5	168.9	178.4	172.8
90 th Percentile	113.5	1.0	30.6	129.4	136.7	132.6
80 th Percentile	69.8	1.0	19.9	86.4	92.4	90.8
50 th Percentile	17.4	0.0	8.4	27.9	32.7	32.4

1-2 “Nested” Bed Policy.

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
Mean	41.5	1.4	12.4	50.6	56.3	53.9
Standard Deviation	54.2	9.7	14.3	58.5	59.7	57.4
99 th Percentile	247.9	19.1	54.0	263.0	268.0	254.1
95 th Percentile	155.0	7.0	34.0	169.6	179.0	172.9
90 th Percentile	113.8	1.0	30.6	129.8	137.0	134.5
80 th Percentile	69.8	1.0	19.5	86.5	92.5	91.0
50 th Percentile	17.4	0.0	8.4	27.9	32.7	32.3

1-3 “Nested” Bed Policy.

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
Mean	41.6	1.4	12.3	50.8	56.5	54.1
Standard Deviation	54.5	9.8	14.2	58.8	60.0	57.7
99 th Percentile	249.2	19.4	53.7	264.4	269.5	254.1
95 th Percentile	155.7	7.0	33.5	170.4	179.9	174.4
90 th Percentile	114.3	1.0	30.6	130.3	137.6	134.9
80 th Percentile	70.0	1.0	19.1	86.7	92.8	91.4
50 th Percentile	17.4	0.0	8.4	27.9	32.7	32.8

1-4 “Nested” Bed Policy.

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
Mean	41.7	1.4	12.1	51.0	56.7	54.2
Standard Deviation	54.8	9.9	14.2	59.2	60.4	58.0
99 th Percentile	250.9	19.1	53.6	266.5	271.6	255.0
95 th Percentile	156.6	7.0	33.0	171.3	180.8	174.6
90 th Percentile	114.8	1.0	30.6	130.9	138.3	135.1
80 th Percentile	70.2	1.0	18.5	87.0	93.3	91.5
50 th Percentile	17.4	0.0	8.4	28.1	32.9	33.0

2-0 “Nested” Bed Policy.

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
Mean	42.5	1.4	13.1	51.7	57.5	55.1
Standard Deviation	56.2	10.1	14.8	60.8	62.0	59.8
99 th Percentile	260.0	14.4	56.2	275.4	282.2	262.5
95 th Percentile	160.3	6.0	35.8	176.4	185.1	181.4
90 th Percentile	116.4	1.0	30.6	133.5	140.9	136.5
80 th Percentile	70.7	1.0	21.1	87.9	94.2	92.1
50 th Percentile	17.5	0.0	8.4	28.5	33.2	33.4

2-1 “Nested” Bed Policy.

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
Mean	42.6	1.4	12.9	51.9	57.7	55.4
Standard Deviation	56.5	10.2	14.8	61.1	62.3	60.2
99 th Percentile	261.1	15.6	55.9	277.0	283.2	263.8
95 th Percentile	161.1	6.0	35.3	177.4	186.0	182.2
90 th Percentile	116.9	1.0	30.6	134.1	141.4	136.9
80 th Percentile	71.0	1.0	20.6	88.2	94.7	92.5
50 th Percentile	17.4	0.0	8.4	28.6	33.4	33.4

2-2 “Nested” Bed Policy.

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
Mean	42.7	1.4	12.7	52.2	57.9	55.7
Standard Deviation	56.8	10.2	14.8	61.5	62.7	60.8
99 th Percentile	262.8	15.6	55.5	278.9	285.1	264.8
95 th Percentile	162.1	6.0	34.8	178.5	187.6	185.8
90 th Percentile	117.5	1.0	30.6	134.9	142.3	139.7
80 th Percentile	71.3	1.0	20.2	88.7	95.2	93.1
50 th Percentile	17.4	0.0	8.4	28.7	33.5	33.5

2-3 “Nested” Bed Policy.

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
Mean	42.9	1.4	12.5	52.5	58.2	56.0
Standard Deviation	57.3	10.4	14.8	62.0	63.1	61.4
99 th Percentile	264.7	15.7	55.4	281.2	288.1	266.6
95 th Percentile	163.3	6.0	34.3	179.9	188.5	187.1
90 th Percentile	118.3	1.0	30.6	135.8	143.4	141.0
80 th Percentile	71.8	1.0	19.7	89.3	95.8	94.1
50 th Percentile	17.4	0.0	8.4	29.0	33.8	33.5

2-4 “Nested” Bed Policy.

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
Mean	43.2	1.4	12.3	52.9	58.6	56.4
Standard Deviation	57.8	10.5	14.8	62.5	63.7	61.8
99 th Percentile	266.9	16.8	55.2	283.4	289.9	267.1
95 th Percentile	164.9	6.0	33.8	181.5	190.3	188.0
90 th Percentile	119.4	1.0	30.6	137.0	144.5	140.4
80 th Percentile	72.4	1.0	19.1	90.1	96.4	94.5
50 th Percentile	17.4	0.0	8.4	29.4	34.3	34.6

A.5 Combined Policy Analysis

Baseline Scenario.

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
Mean	41.4	1.4	12.8	50.4	56.1	53.7
Standard Deviation	53.8	9.7	14.3	58.1	59.2	56.9
99 th Percentile	245.1	19.4	54.6	260.0	265.8	248.7
95 th Percentile	154.0	7.0	34.9	168.5	178.0	173.7
90 th Percentile	113.3	1.0	30.6	129.1	136.3	132.7
80 th Percentile	69.7	1.0	20.4	86.3	92.3	90.8
50 th Percentile	17.4	0.0	8.4	27.9	32.6	32.2

Baseline Scenario +1 Bed.

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
Mean	36.4	1.3	12.1	43.9	49.5	47.4
Standard Deviation	47.7	8.4	13.4	51.7	52.8	50.4
99 th Percentile	219.8	15.2	51.3	234.0	240.8	223.6
95 th Percentile	135.9	6.0	33.5	149.3	157.5	155.5
90 th Percentile	98.3	1.0	30.6	112.9	120.6	117.0
80 th Percentile	64.8	1.0	18.8	72.2	78.1	77.4
50 th Percentile	16.8	0.0	8.4	22.2	29.4	26.4

Baseline Scenario +1 Bed, -5 Minutes for Bed “Flip”.

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
Mean	34.2	1.2	11.8	41.1	46.7	44.6
Standard Deviation	45.2	7.9	12.9	49.0	50.2	47.8
99 th Percentile	210.3	12.0	50.1	224.1	230.8	213.9
95 th Percentile	127.5	6.0	32.3	140.6	148.4	146.3
90 th Percentile	91.1	1.0	30.6	105.1	112.9	109.6
80 th Percentile	64.7	1.0	18.1	65.5	77.4	70.7
50 th Percentile	16.8	0.0	8.4	22.2	29.4	26.4

Baseline Scenario +1 Bed, -5 Minutes for Bed “Flip,” -20 Minutes for Chest Pain

Diagnosis.

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
Mean	32.5	1.1	11.6	38.9	44.5	42.4
Standard Deviation	43.0	7.5	12.6	46.6	47.9	45.2
99 th Percentile	200.4	12.0	49.1	213.9	220.2	204.8
95 th Percentile	120.6	6.0	31.8	133.4	141.4	138.1
90 th Percentile	85.1	1.0	30.6	99.1	106.5	102.4
80 th Percentile	59.5	1.0	17.4	64.8	77.4	66.0
50 th Percentile	16.2	0.0	8.4	22.2	28.7	26.4

Baseline Scenario +1 Bed, -5 Minutes for Bed “Flip,” -20 Minutes for Chest Pain

Diagnosis, +1-2 “Nested” Bed Policy.

	All	ESI-1	ESI-2	ESI-3	ESI-4	ESI-5
Mean	32.6	1.1	11.5	39.0	44.6	42.5
Standard Deviation	43.1	7.5	12.6	46.8	48.1	45.4
99 th Percentile	200.9	12.0	48.9	215.2	221.5	204.8
95 th Percentile	120.8	5.3	31.4	133.7	141.7	138.5
90 th Percentile	85.2	1.0	30.6	99.2	106.7	102.4
80 th Percentile	59.5	1.0	17.0	64.8	77.4	66.0
50 th Percentile	16.2	0.0	8.4	22.2	28.7	26.4

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