Modeling Neuroscience Patient Flow and Inpatient Bed Management

by

Jonas Hiltrop

B.A. Physics, Economics, Macalester College, 2008

Submitted to the MIT Sloan School of Management and the Electrical Engineering and Computer Science Department in Partial Fulfillment of the Requirements for the Degrees of

Master of Business Administration
and
Master of Science in Electrical Engineering and Computer Science

In conjunction with the Leaders for Global Operations Program at the Massachusetts Institute of Technology

June 2014

Signature redacted

Signature of Author____________
MIT Sloan School of Management, MIT Department of Electrical Engineering and Computer Science
May 9, 2014

Signature redacted

Certified by ____________
Retsef Levi, Thesis Supervisor
J. Spencer Standish (1945) Prof. of Management, Assoc. Prof. of Operations Management

Signature redacted

Certified by ____________
David Simchi-Levi, Thesis Supervisor
Professor, Civil and Environmental Engineering and Engineering Systems Division

Signature redacted

Accepted by____________
Maura Herson, Director of MIT Sloan MBA Program
MIT Sloan School of Management

Signature redacted

Accepted by____________
Leslie Kolodziejski, Professor of Electrical Engineering and Computer Science
Graduate Officer, EECS Committee on Graduate Students

This page intentionally left blank.

Modeling Neuroscience Patient Flow and Inpatient Bed Management

by

Jonas Hiltrop

Submitted to the MIT Sloan School of Management and the Department of Electrical Engineering and Computer Science on May 9, 2014 in Partial Fulfillment of the Requirements for the Degrees of Master of Business Administration and Master of Science in Electrical Engineering and Computer Science

Abstract

Massachusetts General Hospital (MGH) experiences consistently high demand for its more than 900 inpatient beds. On an average weekday, the hospital admits about 220 patients, with the emergency department (ED) and the operating rooms (OR) being the main sources of admissions. Given MGH's high occupancy rates, a comparable number of discharges have to occur daily, and the intraday time distributions of admissions and discharges have to be aligned in order to avoid long wait times for beds. The situation is complicated by the specialization of beds and the medical needs of patients, which place constraints on the possible bed-patient assignments.

The hospital currently manages these processes using fairly manual and static approaches, and without clear prioritization rules. The timing of discharges is not aligned with the timing of new admissions, with discharges generally occurring later in the day. For this reason MGH experiences consistent bed capacity constraints, which may cause long wait times for patients, throughput limitations, disruptions in the ED and in the perioperative environment, and adverse clinical outcomes.

This project develops a detailed patient flow simulation based on historical data from MGH. The model is focused on the neuroscience clinical specialties as a microcosm of the larger hospital since the neuroscience units (22 ICU beds and 64 floor beds) are directly affected by the hospital's important capacity issues (e.g., patient overflows into other units, ICU-to-floor transfer delays). We use the model to test the effectiveness of the following three interventions:

1. Assigning available inpatient beds to newly admitted patients adaptively on a just-in-time basis
2. Discharging patients earlier in the day
3. Reserving beds at inpatient rehabilitation facilities, thereby reducing the MGH length of stay by one or more days for patients who need these services after discharge from the hospital

Intervention effectiveness is measured using several performance metrics, including patient wait times for beds, bed utilization, and delays unrelated to bed availability, which capture the efficiency of bed usage.

We find that the simulation model captures the current state of the neuroscience services in terms of intraday wait times, and that all modeled interventions lead to significant wait time reductions for patients in the ED and in the perioperative environment. Just-in-time bed assignments reduce average wait times for patients transferring to the neuroscience floor and ICU beds by up to 35% and 48%, respectively, at current throughput levels. Discharges earlier in the day and multi-day length of stay reductions (i.e., interventions 2 and 3) lead to smaller wait time reductions. However, multi-day length of stay reductions decrease bed utilization by up to 4% under our assumptions, and create capacity for throughput increases.

Considering the expected cost of implementing these interventions and the reductions in patient wait times, we recommend adopting just-in-time bed assignments to address some of the existing capacity issues. Our simulation shows that this intervention can be combined effectively with earlier discharges and multi-day length of stay reductions at a later point in order to reduce wait times even further.

Thesis Supervisor: Retsef Levi
J. Spencer Standish (1945) Prof. of Management, Assoc. Prof. of Operations Management

Thesis Supervisor: David Simchi-Levi
Professor, Civil and Environmental Engineering and Engineering Systems Division

This page intentionally left blank.

The author wishes to acknowledge the Leaders for
Global Operations Program for its support of this work.

This page intentionally left blank.

Acknowledgements

This project would not have been possible without the support of many people. First and foremost, I would like to thank Professor Retsef Levi for guiding this project from beginning to end. His technical competence and tireless devotion have been crucial to its success. It has been an incredible experience to work with him. I would also like to thank Professor David Simchi-Levi for his feedback and advice, which greatly improved the quality of the final project.

I owe many thanks to numerous individuals at Massachusetts General Hospital. Thank you to Dr. Peter Dunn and Bethany Daily for their enthusiastic support of the MIT – MGH collaboration in general, and this project in particular. Dr. Peter Dunn provided valuable clinical insights and feedback on all parts of this project. He and Bethany Daily were instrumental in establishing connections to various individuals in the neurosciences, Admitting, the ED, and the perioperative environment. Their championing of this research among MGH's various stakeholders has opened many doors and pushed this project forward. I would also like to thank Bethany Daily for her input and feedback, which have greatly improved the quality and clarity of my thesis.

Dr. Wilton Levine allowed me to shadow him and answered many of my clinical questions. Brianna Germain provided important administrative support, helped me set up meetings, and made sure that I had everything I needed. I am indebted to Marina Maziya for her perpetual willingness to respond to my seemingly never-ending data requests and inquiries. Similarly, Bhrunil Patel went out of his way to help gather the Patcom data. Thank you to Maureen Schnider and the nursing supervisors, as well as Ben Orcutt and the Admitting staff, for helping me understand the bed management and assignment processes.

I would also like to thank the clinicians and administrators in the neurosciences at MGH for their support. Both Dr. Emad Eskandar and Dr. Lee Schwamm helped me understand the organizational structure of the department and offered feedback on my analyses and ideas. Furthermore, I am grateful to the nurses and administrative assistants for allowing me to shadow them and for taking the time to explain the work processes on Lunder 6, 7, and 8.

In addition, I owe much to the support of MIT post-docs David Scheinker and Cecilia Zenteno. David provided valuable practical guidance throughout the implementation of the model. He spent countless hours helping me resolve data issues and technical problems. I could not have completed this project without his hands-on assistance. Cecilia's wealth of knowledge and willingness to help with tasks large and small allowed me to overcome many obstacles. She was also a valuable sounding board for my ideas and results.

Finally, I would like to thank my family and friends for their support. To my parents, Andrea and Peter, and my sisters, Rebecca and Raphaela, thank you for the moral support that allowed me to complete this research and write this thesis. Yael, thank you for your encouragement throughout this project, and your detailed review of my thesis drafts. Last but not least, thank you to all my other friends for excusing me at all the events that I had to miss because of this project. I greatly appreciate it.

This page intentionally left blank.

Table of Contents

List of Figures

List of Tables

1 Introduction

The work in this project is the first effort of the MIT – MGH collaboration to develop predictive models, decision support tools, and new processes for managing the hospital's more than 900 hospital beds more effectively. The work is a significant first step towards the development of a hospital-wide dashboard that can provide decision makers at Massachusetts General Hospital (MGH) with information about the current state and the predicted future state of bed resources. This information will enable stakeholders to manage available resources effectively, anticipate capacity constraints, and address these constraints before they happen.

This project, which was carried out under institutional review board (IRB) approval, is focused on the neuroscience medical services (i.e., neurology and neurosurgery) at MGH since these services can be studied as a microcosm of the larger hospital. The neurosciences share 22 intensive care unit (ICU) beds and 64 floor beds, and serve both surgical and medical patients who are admitted either electively or through the emergency department (ED). The neuroscience units experience high volume demand for inpatient beds, causing long wait times and flow disruptions for patients. Since many of these capacity issues also affect other parts of the hospital, new processes that prove successful in the neurosciences would likely also benefit other clinical specialties.

Given the significant cost and effort required to implement new management approaches in a large and complex organization like MGH, it is important to study the effectiveness of new approaches carefully before any changes are made. In this thesis, data-driven simulation and other analytical approaches are used to carry out this type of evaluation. The results of these analyses will be used in order to prioritize the implementation of different interventions through pilot studies in the neurosciences. These pilot studies will provide a better understanding of the most promising directions.

1.1 Massachusetts General Hospital

Massachusetts General Hospital (MGH) is the third oldest hospital in the United States and the oldest and largest hospital in New England. It is consistently placed among the top hospitals on the U.S. News & World Report Best Hospitals Honor Roll. In 2013, MGH was ranked second in the nation and first in New England based on its quality of care, patient safety, and reputation in 16 clinical specialties. The hospital admits approximately 48,000 inpatients per year, handles more than 1.5 million outpatient visits, records 90,000 emergency room visits, and performs more than 37,000 surgeries. In addition to world-class patient care, MGH also conducts the largest hospital-based research program in the United States and is the original and largest teaching hospital of Harvard Medical School.

1.2 MIT – MGH Collaboration

The MIT – MGH Collaboration is a partnership between MGH and the Massachusetts Institute of Technology (MIT). The collaboration focuses on improving the operational effectiveness of the hospital. Formed over seven years ago, the collaboration comprises MIT faculty, members of the MGH leadership, post-doctorate students within the Operations Management group at the MIT Sloan School of Management, and students in the MIT Leaders for Global Operations (LGO) program.

The partnership initially focused on studying and implementing changes in the hospital's perioperative environment. To this end, several previous projects examined ways to improve surgical scheduling, patient flow, as well as other operational aspects. The current project extends the previous work of the MIT – MGH collaboration to the neurosciences (i.e., neurology and neurosurgery) by developing a comprehensive patient flow model that encompasses not only the perioperative environment, but also the ED and the different neuroscience inpatient floors and ICUs.

1.3 MGH Neuroscience

The MGH neuroscience clinical specialties comprise the hospital's neurology and neurosurgery departments, which in turn are made up of several different services that focus on specific medical sub-specialties (i.e., teams of care providers organized around certain types of clinical conditions). Like other clinical specialties, the neurosciences serve a variety of patient populations. While the ED and the operating rooms (OR) are the main sources of admissions, the neurosciences also serve patients coming from other care facilities and front door (i.e., scheduled) clinical admissions.

The neuroscience specialties currently share a total of 86 inpatient beds. These include 22 intensive care beds, as well as 64 floor beds. In 2012, approximately 1,700 patients stayed in the neuroscience ICU and approximately 5,000 patients stayed on the two neuroscience floors.

1.4 Project Overview

1.4.1 Problem Statement

The neuroscience units at MGH experience high volume demand for inpatient beds from the ED, from the operating rooms (OR), from front door clinical admissions, and from hospital in-transfers. As a result, these units experience consistently high occupancy rates. In this situation, the number of discharges must closely match the number of new admissions each day in order to accommodate all newly admitted patients. In addition, the intraday distributions of admission and discharge times have to be aligned in order to avoid long patient wait times for beds. Patient wait times for beds may potentially have significant negative impacts on patients' experiences and clinical outcomes. Moreover, patients waiting in the ED or the post-anesthesia care units (PACU) can seriously disrupt hospital operations. For example, if the ED is overly crowded, the hospital may have to go into Code Help and cancel elective surgeries.[1] PACU overcrowding can also lead to surgery cancellations. The situation is further complicated by hospital bed specialization and the medical needs of patients, which constrain the possible bed-patient assignments.

[1] Code Help is a state-mandated policy requiring hospitals to move all admitted patients out of the ED within a 30-minute period after the ED's maximum occupancy is reached or exceeded. A prolonged Code Help requires the hospital to make a report to government officials and might require the ED to divert patients to other hospitals.

Currently, discharges and bed assignments for new admissions at MGH are managed with manual and relatively static processes, and without clear prioritization rules. The timing of discharges is largely disconnected from the timing of new admissions, with discharges generally occurring later in the day. As a result, the hospital experiences consistent bed capacity constraints, which cause long intraday wait times and multi-day delays for patients, and may result in suboptimal bed assignments and throughput limitations.

Observations at the hospital, and interviews with relevant stakeholders, revealed the following challenges that affect the neurosciences as well as many other clinical specialties and departments at the hospital:

- The bed assignment process is highly decentralized and not standardized. Patient placements are negotiated daily on a case-by-case basis between the Admitting department ("Admitting") and clinical staff in the inpatient units. While Admitting is responsible for matching newly admitted patients to beds, the beds in the inpatient units are managed by the respective floor and ICU staff.
- Bed-patient assignments are made without access to all relevant information, such as timing of discharges, front door admissions, surgeries, and ED procedures. No transparent guidelines exist on how to prioritize assignments. As a result, assignments are often made prematurely (i.e., before the bed is cleaned and/or the patient is ready to occupy the bed). Adaptive re-assignments generally do not happen even if they could reduce both patient wait times and bed idle times.
- Discharges are generally not processed until late in the day. Care providers prioritize inpatient care and teaching activities throughout the morning over discharging patients. This contributes to a misalignment in the intraday timing of admissions and discharges.
- Patients who need continued inpatient care after discharge from MGH experience multi-day discharge delays due to capacity constraints at suitable long-term care facilities (e.g., skilled nursing facilities, long-term care hospitals, rehabilitation hospitals, etc.). The extended stay of these patients directly limits the number of beds available to new admissions on any given day.

1.4.2 Goals

This project aims to develop better and more systematic bed management approaches, align the intraday distributions of admissions and discharges, reduce non-clinical, multi-day discharge delays, and effectively allocate hospital beds to patients. The goal is to test new operational approaches using a comprehensive patient flow model for the neuroscience clinical specialties at MGH. The model encompasses the perioperative environment, the ED, and the different neuroscience inpatient floors and ICUs. The neuroscience clinical specialties at MGH represent a microcosm of the entire hospital because these specialties have their own dedicated inpatient units that are directly affected by all major capacity issues at the hospital (e.g., patient "overflows" into other units, ICU-to-floor transfer delays, discharge delays, etc.) and that serve both surgical and medical patients. Focusing on these units allows us to analyze the capacity issues of the entire hospital and test potential interventions in a relatively contained setting.

Modeling the MGH neuroscience patient flow in its entirety enables us to test a wide variety of potential operational improvements. While previous studies have primarily focused on investigating the effects of operational changes on patient flow in a particular part of the hospital (e.g., the ED, the perioperative bays, or the ORs), our model makes it possible to analyze the effects of such changes across different departments. Furthermore, the model provides the ability to test more complex interventions such as just-in-time bed placements for newly admitted patients. These interventions involve changes in more than one department of the hospital and can therefore only be studied accurately by looking at the overall patient flow from admission to discharge.

1.4.3 Approach

We develop a data-driven simulation that can be used to analyze the current state of patient flow and to evaluate the impact of new operational approaches. While the model is flexible enough to model a wide variety of potential interventions, this project is focused on three specific interventions that are designed to address some of the most pressing capacity issues:

1) **Just-in-time bed assignments:** Allocate available inpatient beds to patients using a just-in-time algorithm that assigns beds adaptively only to patients who are ready to move to the bed.
2) **Discharges earlier in the day:** Process discharges earlier in the day in order to align the intraday timing of discharges with the timing of new admissions.
3) **Multi-day Length of Stay Reductions:** Reserve beds at inpatient rehabilitation facilities, thereby reducing the MGH length of stay by one or more days for patients who need these services after discharge from the hospital.

The following performance metrics are used to evaluate and compare the effectiveness of different process interventions:

1) **Intraday patient wait hours for beds in the ED, ORs, and PACUs:** Time from patients' medical readiness to be transferred to a bed to the time a bed is cleaned and assigned to the patient. This metric does not include additional transfer processing wait times incurred after the patient is ready and a clean bed is assigned to the patient since transfer processing wait times are not associated with bed management practices.
2) **Cumulative delay unrelated to bed availability (DUBA):** Cumulative number of hours that patients spend waiting while suitable beds are available (i.e., clean).
3) **Bed utilization:** Fraction of time that floor and ICU beds are occupied or in cleaning.

By measuring the effect of the interventions on these performance metrics, it is possible to predict how much existing processes will have to change in order to remove current bottlenecks. For example, the model aims to answer the following question: How many patients will have to be discharged earlier (and by how much) in order to overcome bottlenecks in the PACU and the ED?

The distinction between intraday delays and interday (or multi-day) delays is important. Intraday delays occur as a result of temporary capacity constraints during peak hours of the day. These capacity constraints create wait times for patients who need to be transferred from one department (e.g., the ED or the perioperative environment) to another department (e.g., a hospital floor or ICU), which is currently capacity constrained. Intraday delays can result from both bed capacity-induced constraints and from inefficient bed management approaches that create delays unrelated to bed availability. In addition, these delays may have a negative impact on clinical outcomes and cause flow disruptions in the ED and the perioperative environment.

Multi-day delays on the other hand result from long-term, capacity-induced constraints in certain parts of the hospital (e.g., a hospital floor). These chronic capacity issues can delay patient transfers between different parts of the hospital for several days or prohibit them entirely. Multi-day delays are most relevant for patients waiting for ICU-to-floor transfers and other patients waiting to transfer between different inpatient units. Meanwhile, intraday delays affect all parts of the hospital (i.e., the ED, the perioperative environment, and inpatient units). While we distinguish between multi-day and intraday delays, we also note that multi-day delays can indirectly affect intraday delays and vice versa.

The work in this thesis focuses primarily on eliminating intraday delays through changes to the bed management approach. While the effective intraday management of bed resources also benefits patients affected by multi-day delays, these benefits are only addressed tangentially in this study due to lack of necessary data. The detailed study of multi-day delays is the subject of ongoing work by the MIT – MGH collaboration.

1.4.4 Results

The patient flow model is validated using historical data from the ED and the perioperative environment. We find that the distributions of patient wait times in the current state model are not statistically different from their true historical distributions.

All three interventions analyzed in this study lead to significant wait time reductions for patients in the ED and in the perioperative environment. While wait time reductions for patients transferring between different inpatient units and for clinical front door admissions cannot be quantified accurately using our model, we find that these patient populations also benefit from the interventions.

Considering both the expected cost of implementing different interventions and the reductions in patient wait times, we find that adopting just-in-time bed assignments would be the most expedient intervention to address existing capacity issues. Discharges earlier in the day and multi-day length of stay reductions for patients discharged to other care facilities generally yield more moderate wait time reductions at current throughput levels. However, in conjunction with just-in-time bed assignments, these interventions can lead to significant additional decreases in wait times.

Just-in-Time Bed Assignments

Just-in-time bed assignments reduce average bed wait times for patients transferring from the ED and the perioperative environment to floor beds by approximately 35% (68 minutes and 35 minutes, respectively) compared to current state levels. Average bed wait times for ED patients requiring ICU-level care decrease by 48% (42 minutes). Patients with exceptionally long wait times in the current state experience the largest wait time reductions while patients with zero or very short wait times in the current state see their wait times increase marginally.

The longest wait times for floor and ICU patients in the ED decrease by more than three hours and two hours (22% and 38%), respectively. Meanwhile wait times for patients with zero or very short wait times in the current state increase slightly (i.e., the 5^{th} percentile increases from zero minutes to seven minutes for both floor and ICU patients), implying that the overall distribution of wait times across patients becomes more equitable.

Surgical patients requiring ICU-level care experience non-zero wait times slightly more frequently when ICU beds are assigned on a just-in-time basis. While this is undesirable, the problem can be addressed by accommodating affected patients in PACUs or by making minor modifications to the bed assignment algorithm.

Discharges Earlier in the Day

Wait time reductions resulting from earlier discharges alone are lower than reductions achieved through just-in-time bed assignments. Shifting the average discharge times forward by more than three hours decreases average wait times for floor and ICU patients in the ED by 26% (50 minutes) and 15% (13 minutes), respectively, compared to the current state. The average wait time for surgical patients transferring to floor beds decreases by 33% (30 minutes). Surgical patients requiring ICU-level care do not see meaningful wait time reductions.

We find that the additional capacity generated through earlier discharges does not fully line up well with the timing of bed needs for newly admitted patients. In addition, the current bed assignment process at the hospital diminishes the effectiveness of earlier discharges. However, earlier discharges can be combined effectively with just-in-time bed assignments to produce more significant wait time reductions.

Multi-Day Length of Stay Reductions

Discharging a quarter of patients with longer term care needs four days earlier to post-MGH care facilities reduces average intraday wait times in the ED for patients transferring to floor and ICU beds by approximately 35% (68 minutes) and 12% (ten minutes), respectively. Average wait times for surgical patients transferring to floor and ICU beds decrease by approximately 31% (40 minutes) and 64% (nine minutes), respectively.

The factors that limit wait time reductions achieved through earlier intraday discharges also limit the effectiveness of multi-day length of stay reductions. The latter intervention is therefore found to be more appropriate for increasing patient throughput than for reducing intraday wait times at current throughput levels. Discharging a quarter of patients with continued inpatient care needs four days earlier reduces unit bed utilization by more than 4%, implying that a significant number of additional patients could likely be accommodated.

1.5 Thesis Outline

The thesis project is organized as follows. Section 2 provides a review of relevant studies in the existing literature, including previous published research of the MIT – MGH collaboration and related studies by other researchers. Section 3 provides a comprehensive current state analysis of the neurosciences at MGH (Section 3.2) and the bed management process (Section 3.3). This section also discusses the three key challenges that we aim to address (Section 3.4). Section 4 develops the modeling framework used for the data-driven patient flow simulation. It discusses the data sources used in the simulation (Section 4.2), the modeling approaches for the ED, the perioperative environment, and the inpatient units (Section 4.3), the performance metrics tracked in the simulation (Section 4.4), and the model implementation of different process interventions (Section 4.5). Section 5 discusses the results of the current state model (Section 5.1) and the intervention models (Sections 5.2 – 5.5). Section 6 makes recommendations for the implementation and prioritization of different interventions based on the simulation results (Section 6.1), and provides ideas for further study (Section 6.2).

2 Literature Review

Several projects of previous LGO students in the MIT – MGH collaboration developed important insights into the patient flow dynamics and work processes at MGH. One set of projects focused on improving surgical patient flow at the hospital. Price (2011) aimed to reduce the number of patients in the hospital overnight (i.e., the midnight census) by optimizing the assignment of operating rooms and operating times to surgeons. Each surgeon at MGH is given access to a specified operating room on certain days of the week, allowing her to schedule surgeries for her patients. The organization of the resulting overall OR schedule has significant impact on inpatient volume on different days of the week. Price rearranged the assignment of operating dates and times to surgeons in order to reduce peak occupancy rates that occurred in the middle of the week.

Range (2013) extended this work by developing OR case scheduling heuristics that reduce the midday peak occupancy in the perioperative environment of the hospital. To this end, she tested different approaches for arranging the order of different types of surgical cases in the daily OR schedules (i.e., shortest cases first, longest cases first, outpatients first, etc.). She found that midday peak occupancy rates can be reduced by scheduling surgeries of same-day admissions, observation patients, and outpatients requiring a bed after surgery last in the daily OR schedules.

A third project developed more efficient approaches for scheduling unplanned (i.e., non-elective) surgeries for patients from the ED and the different hospital inpatient units. Under the current system, these patients are placed on a waitlist and then scheduled for surgery within a certain time interval depending on the severity of their condition, surgeon availability, and OR room availability. The project investigated approaches for reducing the time it takes for non-elective patients to be scheduled for surgery. The research resulted in the creation of reserved OR times (so-called open blocks) which are accessible to groups of surgeons in order to handle non-elective surgeries.

The current study extends the existing research in the perioperative environment to the neurosciences at MGH. The insights gained by Range (2013) and Price (2011) about surgical patient flow inform the model of the perioperative environment developed as part of the current study. This project also further investigates some of the challenges with current bed management and discharge processes discovered by previous researchers (i.e., discharge delays and inefficient prioritization of bed-patient assignments).

Another ongoing research initiative of the MIT – MGH collaboration investigates transfer delays for patients who are medically ready to be transferred from an ICU bed to a floor bed. Christensen (2012) studied the latter problem in the surgical intensive care unit (SICU) at MGH. He developed a discrete event simulation of the SICU and six primary downstream units in order to test new operational approaches and reduce ICU-to-floor transfer delays. He finds that existing delays can be reduced significantly by transferring patients from the SICU to a floor as soon as possible (i.e., eliminating the current practice of waiting to see if other patients need downstream beds), and implementing a 24-hour rolling medical clearance process in the SICU.

The neuroscience patient flow simulation developed in the current study incorporates the lessons learned by Christensen about the unit-to-unit transfer process, the discharge process, and the bed assignment process. His findings also inform our modeling assumptions about patients' medical readiness for transfer. Finally, our simulation approach uses the same modeling environment and some of the same data sources as Christensen (2012) and Range (2013), and we utilize several of the same modeling techniques.

A number of studies by other researchers have also addressed the challenge of managing bed resources in hospital environments. One focus of the literature has been on analyzing the connection between discharge timing and capacity constraints. Powell et al. (2012) investigate the relationship between inpatient discharge timing and emergency department boarding using a cross-sectional computer modeling analysis. The study tests different alternative intraday discharge schedules and finds that discharges earlier in the day reduce or eliminate ED boarding. Hendy et al. (2012), Majeed et al. (2012), as well as several other research groups quantify the number of avoidable bed-days and the additional cost resulting from intraday and multi-day discharge delays in specific hospitals. While these studies identify some of the reasons underlying the delays, they generally do not propose specific solutions. Borghans et al. (2012) propose a multitude of approaches for addressing discharge delays and reducing lengths of stay. However, the effectiveness of the proposed solutions is not quantified and prioritization of the different interventions is therefore not easily possible.

Our project expands on this literature by investigating the effect of intraday discharge timing and patient length of stay on wait times throughout the hospital, including the ED and the perioperative environment.

We propose specific interventions to eliminate delays and we quantify the effectiveness of the proposed approaches, allowing stakeholders to prioritize the implementation of different interventions.

A second branch of the literature examines strategies to improve throughput and quality of care through modifications to the admission and bed assignment processes. Among other studies, Thomas (2013), Schmidt et al. (2013), and Bachouch et al. (2012) analyze specific decision support tools and algorithms for assigning available beds to patients. Griffiths et al. (2013) propose a model for improving bed management and smoothing occupancy levels by distinguishing between elective and non-elective admissions, and making the admission of elective patients dependent on current occupancy levels.

These studies inform the bed assignment and bed management approaches proposed in our study. However, the tools and algorithms developed by these researchers cannot be applied directly to the neurosciences at MGH due to limitations in the availability of real-time data in the bed assignment process at MGH. We therefore propose a different bed assignment approach that does not rely on accurate information about expected admissions and discharges or patients' expected lengths of stay.

3 Current State Analysis

3.1 Introduction

This section provides a comprehensive current state analysis of the neuroscience patient flow at MGH (Section 3.2) and the associated bed management processes (Section 3.3). The analysis was conducted through numerous interviews with administrative and clinical stakeholders, as well as through the observation and documentation of work processes in different departments (i.e., the ED, the perioperative environment, and the neuroscience units). We corroborated the observations made during this process through the analysis of historical data from several data sources, including the emergency department information system (EDIS), the perioperative data systems, the Admitting data system (Patcom), and the bed management system (CBEDs). This approach allowed us to map the existing bed management processes at the hospital, including their limitations, needs, performance metrics and gaps. The findings of the current state analysis inform the modeling approach for the simulation developed in Section 4, and the key challenges of the current process (Section 3.4) motivate the design of the process interventions that are tested using the simulation.

3.2 MGH Neuroscience

Figure 1 shows an organizational overview of the neuroscience clinical specialties at MGH.

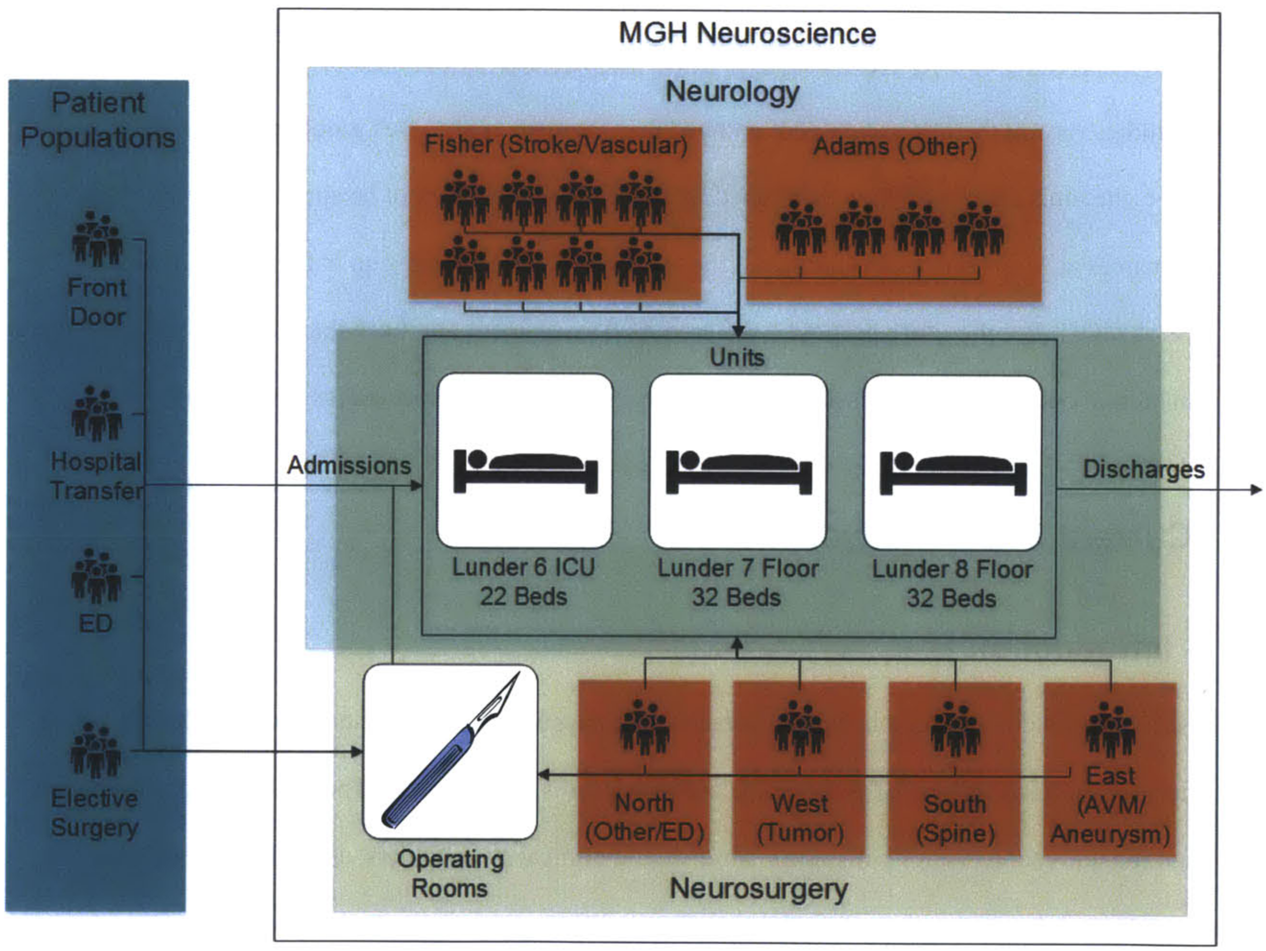


Figure 1 - MGH Neuroscience Overview

The MGH neuroscience clinical specialties comprise the hospital's neurology and neurosurgery departments. As shown in Figure 1, both departments encompass several different services (i.e., teams of care providers) that focus on specific medical sub-specialties. The neurology services are named "Fisher" and "Adams." These services focus on vascular (including stroke) disorders and other neurological disorders, respectively. A separate team of intensivists (i.e., the "Young" service, not shown in Figure 1) staffs the neuroscience ICU. Neurology patients who visit both the neuroscience ICU and a floor during their stay at MGH are consequently cared for by different services at different times.

The four neurosurgery services are referred to as "West," "South," "East," and "North." Generally speaking, these services focus on tumors, disorders affecting the spine, arteriovenous malformations (AVMs) and aneurysms, and ED patients and other neurosurgical diagnoses, respectively. Unlike neurology patients, neurosurgery patients are cared for by the same service both in the ICU and on the floors (i.e., throughout their entire stay).

The neuroscience specialties currently share a total of 86 inpatient beds on three different levels of the new Lunder building, which opened on MGH's main campus in the beginning of September 2011. The total bed capacity includes 22 intensive care beds in the neuroscience ICU on the 6th floor ("Lunder 6 ICU"), as well as 64 floor beds on the 7th and 8th floors ("Lunder 7 and 8 Floors"). All of the Lunder patient rooms are private, single-patient rooms. Patients' precautions and gender-matching of roommates therefore do not need to be considered during the patient placement process.

Like other clinical specialties, the neurosciences serve a variety of patient populations. The ED and the ORs are the main sources of admissions. Non-elective (i.e., emergency) patients are admitted to the appropriate neuroscience service through the ED. Once the attending physician in the ED decides that a patient has to be admitted to the hospital, she requests an appropriate bed for the patient. Furthermore, a surgery time may be booked for patients requiring surgery.

The bed request, which is sent electronically to Admitting, includes the type of bed requested for the patient (i.e., ICU bed or floor bed), as well as the clinical service that the patient is being admitted to (e.g., Adams, North, etc.). A bed manager in Admitting then finds an available bed for the patient and electronically assigns the patient to the unit where the bed is located.[2] An administrative assistant ("operations assistant" or "OA") in that unit then assigns a specific bed to that patient (i.e., reserves the bed). See Section 3.3 for a detailed discussion of this process. ED patients may either be transferred directly from the ED to a neuroscience inpatient bed (e.g., in the case of neurology patients), or patients may be transferred via the OR (e.g., in the case of neurosurgery patients requiring immediate surgery).

Elective surgery patients are admitted to the neurosciences via the perioperative environment. These patients generally arrive at the hospital on the day of surgery. The daily surgery schedule specifies the anticipated type of bed needed for each elective surgery patient. This information is used by Admitting in order to assign these patients to units where beds are (expected to become) available. Most elective patients requiring ICU-level care after surgery are transferred directly from the OR to a bed on Lunder 6. Floor patients are generally brought to a perioperative bay for immediate post-anesthesia care before they are transferred to a bed on Lunder 7 or 8.

The neurosciences also serve patients coming from other care facilities and front door (i.e., scheduled) clinical admissions. Transfers from other hospitals are facilitated by a designated bed manager in Admitting (called "MD Connect"). All transfer requests have to be approved by the medical or surgical service at MGH that is going to receive the patient. If the request is approved, a bed manager in Admitting and an OA in the destination inpatient unit at MGH assign an appropriate bed to the patient and the transfer is carried out.

Front door clinical patients are admitted to the neurosciences via locations other than the ED or the OR (e.g., the catheterization laboratory or a hospital-internal clinic). Bed managers use the daily admission schedule to determine the bed needs of these patients, and to assign these patients to appropriate inpatient units.

---

[2] For patients requiring ICU-level care, assignments are made in consultation with the nursing supervisors, who are responsible for making ICU patient placement decisions.

In addition to new admissions, hospital-internal transfer patients also compete for space in the three neuroscience units. Most importantly, patients in the ICU should be transferred to a floor bed once their medical conditions improve sufficiently. Floor patients may also have to be transferred to the ICU due to deteriorations in their medical conditions. OAs in the different neuroscience units electronically request patient transfers in Admitting via the hospital's bed management system CBEDs. Depending on bed availability, transfer patients may be assigned to beds in their target units, the bed requests may be held, or the bed request may be canceled.

Patients depart the neuroscience inpatient units when they are discharged or when they are transferred to another clinical specialty at MGH. OAs on the floors and in the ICU inform Admitting about upcoming discharges electronically via CBEDs. After a patient is discharged, the OA requests a bed cleaning via CBEDs. Once the cleaning is completed, the bed is ready for the next patient.

3.3 Bed Management Process

On an average weekday, MGH admits about 220 elective and non-elective patients, with the ED and the ORs being the main sources of admissions. All of these patients have to be matched to appropriate hospital beds in a timely manner. The situation is complicated by the specialization of hospital beds, the medical needs of patients, and the hospital's consistently high occupancy rates, which place additional constraints on the possible bed-patient assignments.

3.3.1 CBEDs

MGH uses a bed management system called CBEDs to manage its more than 900 hospital beds. CBEDs provides a graphical user interface with detailed information about the current status of every bed. The system distinguishes between the following bed statuses:

- Occupied: A patient is currently occupying the bed.
- Dirty: The bed is not occupied by a patient and needs to be cleaned.
- In cleaning: The bed is not occupied by a patient and currently being cleaned.

- Clean: The bed is not occupied by a patient and clean (i.e., ready for occupancy).
- Closed: The bed is unavailable due to staffing shortages, repairs, maintenance, or other reasons.

Each status in CBEDs can be combined with the following additional information:

- Assignment: The bed can be assigned to a waiting patient. This applies to beds that are available (i.e., clean) or expected to become available in the foreseeable future.
- Time to discharge: This specifies the number of hours until the current occupant is expected to be discharged and applies to beds whose current occupants are expected to be discharged on the current day.
- Precautions: Medical precautions for the current occupant of the bed can be specified.
- Additional information: The reason for why a bed is closed, specific bed features that have been activated, etc. can be specified.

The addition of this information to the current bed status is optional and not always performed. For example, the time to discharge is not consistently entered into CBEDs for all anticipated discharges on any given day.

The information in CBEDs is updated by bed managers in Admitting, OAs in the different inpatient units, and bed cleaners. Bed managers assign newly admitted patients and internal transfers to specific inpatient units in CBEDs. The OAs confirm these unit assignments by matching patients assigned to their units to specific beds that are available or expected to become available. In addition, OAs enter information about (expected) departures from their units into CBEDs. This action generates a bed cleaning request in the bed cleaning department and lets Admitting know that a bed is going to become available. Bed cleaners update the bed status when cleanings are started and completed using a phone dial-in system that is linked up with CBEDs.

3.3.2 Bed Assignment Process

Throughout the day, OAs on the floors and in the ICUs notify bed managers about upcoming (or currently occurring) discharges through CBEDs. At the same time, bed managers receive bed requests for newly admitted patients from a variety of sources. The ED notifies bed managers about unscheduled admissions through the ED information system ("EDIS"). In addition, bed managers receive daily admission reports with all scheduled admissions. Using the various sources of information, bed managers then have to determine how to allocate available beds to newly admitted patients.

Bed managers follow a general set of guidelines to prioritize bed assignments among patients admitted to the same medical service and level of care (i.e., ICU vs. floor). Surgical and clinical elective admissions are generally prioritized based on the scheduled start times of their procedures. These patients tend to be matched to available beds (or beds that are known to become available later in the day) at the start of the morning shift.

Meanwhile, ED admissions are prioritized based on their arrival time at the hospital.[3] After the attending physician in the ED determines that a patient will have to be admitted, the ED places an electronic bed request in the Admitting department. Admitting then assigns these patients to beds throughout the day.

New admissions have higher priority than other patient populations (e.g., ICU-to-floor and other unit-to-unit transfers) since internal transfer patients already have a place at the hospital. MGH-internal transfers tend to be processed after all elective and non-elective admissions for the day have been placed unless the beds currently occupied by the transferring patients are needed for new admissions.

While bed managers in Admitting and OAs in the inpatient units are responsible for carrying out unit and bed assignments in CBEDs, respectively, the decision-making authority in the bed assignment process is highly decentralized. The beds in the inpatient units are managed by the respective floor and ICU staff.

[3] These rules serve as guiding principles. However, they are not strictly imposed and deviations from these guidelines do occur. For example, if a patient's surgery is expected to take an unusually long time, the patient's bed assignment might be deprioritized since the patient will not be ready to occupy the bed for an extended period of time.

Therefore, patient assignments to any specific bed have to be approved by the staff in the unit where the bed is located. In addition, ICU bed assignments are decided (in collaboration with the respective ICU staff) by the nursing supervisors. These decisions are then communicated to the bed managers in Admitting, who implement the decisions in CBEDs.

3.3.3 Bed Management Meetings

Several daily, in-person meetings facilitate decision-making in the current bed assignment process. The following meetings are most relevant to the neuroscience patient flow.

ICU Bed Capacity Meeting (7:45 AM)

This meeting focuses on elective surgery patients who will require an ICU bed after surgery. The meeting is attended by the critical care nursing supervisor, resource nurses from all surgical ICUs except the Cardiac Surgery ICU (i.e., the SICU on Ellison 4, the ICU on Blake 12, and the Neuroscience ICU on Lunder 6), the Floor Walker, and a resource nurse from the PACU on Ellison 3.[4]

All attendees have gone through the daily OR schedule prior to meeting and tallied up ICU bed requests of surgical patients. Participants compare results and discuss whether or not any additional surgical patients who do not have ICU bed requests may need ICU beds (based on type of surgery). The Floor Walker also provides an update on surgical patients who have ICU bed requests but may no longer need ICU beds. The resource nurses provide capacity updates from their ICUs and indicate whether or not they expect ICU bed shortfalls given expected departures (i.e., discharges and ICU-to-floor transfers) and expected admissions (i.e., outstanding bed requests for beds in their units).

Unit assignments for elective surgery patients with ICU bed needs are decided based on patients' medical needs, the timing of surgeries, and the bed capacity updates from the different ICUs. After completion of the meeting, the nursing supervisor meets with bed managers in Admitting to inform the bed managers

[4] The Floor Walker is a senior anesthesiologist who manages the ORs and the OR schedule. This role rotates daily. The PACU on Ellison 3 is currently the only PACU at MGH that is open overnight. The PACU can accommodate overnight ICU patients if needed. No representative from the Cardiac Surgery ICU attends the meeting since this unit manages its beds relatively independently.

about the unit assignment decisions.[5] The bed managers then carry out the unit assignments in CBEDs. Meanwhile, the ICU resource nurses make specific bed assignment decisions for all new admissions to their units. They communicate these decisions to the OAs in their units. The OAs approve the unit assignments made by Admitting and assign patients to specific beds in CBEDs.

Neuroscience Bed Meeting (9:15 AM, Lunder 8 Conference Room)

This meeting focuses on the daily patient flow in the neuroscience units (i.e., Lunder 6, 7, and 8). The meeting is attended by the resource nurses from the neuroscience units and the Admitting bed manager who is responsible for neuroscience bed assignments.[6] The resource nurses provide updates on current bed availability and expected discharges from their units. The Lunder 6 resource nurse also goes over patients who are ready to be transferred from the ICU to a floor. The Admitting bed manager lists outstanding neuroscience floor bed requests for elective surgery and ED patients.

The bed requests are prioritized depending on their timing and urgency. Empty beds on Lunder 7 and 8 are generally first allocated to ED and elective surgery patients. If the number of available beds exceeds the number of bed requests, remaining beds are given to ICU patients waiting for an ICU-to-floor transfer.[7] After the meeting, the bed manager carries out the assignment decisions that were made during the meeting in CBEDs.

Hospital-Wide Bed Capacity Meeting (10:00 AM, Admitting Conference Room)

This is a big-picture meeting that generally lasts about five to ten minutes unless serious capacity concerns exist or are expected later in the day. The meeting is intended to inform stakeholders from different parts of the hospital about the current capacity situation, and to actively manage acute situations

[5] After meeting with the bed managers in Admitting, the nursing supervisor also visits the ED to inform the ED staff about current bed availability in the different ICUs. The information is communicated to the ED staff for their reference. In general, no specific decisions are made during this visit.

[6] Each bed manager in Admitting is responsible for managing bed assignments in specific inpatient units and for specific patient populations. The assignment of responsibilities rotates daily. Hence, different bed managers attend the neuroscience bed meetings depending on what day it is.

[7] Bed requests from patients waiting for ICU-to-floor transfers may be prioritized over bed requests from elective surgery and ED patients if the Lunder 6 ICU is experiencing acute capacity constraints.

like Code Help. Attendees vary, but they generally include a nursing supervisor, a senior representative from Admitting, resource nurses from several different floors and ICUs, a representative from Case Management, and the Floor Walker.

Admitting presents the morning capacity report, which lists current occupancy statistics for inpatient floors and ICUs, patient volumes in the ED and the PACUs, current capacity concerns, average admissions and discharges for the current weekday, as well as scheduled admissions and discharges for today and the next four weekdays. Capacity constraints in specific units are pointed out by Admitting or the resource nurses from those units.

3.4 Key Findings

3.4.1 Prioritization of Bed-Patient Assignments Not Based on Patient Readiness

As a result of the bed management approaches discussed in Section 3.3, bed assignments are frequently made prematurely in the sense that they precede the bed's or patient's actual readiness to be matched (e.g., the bed is still occupied by another patient or has not yet been cleaned).

We note that in some cases there are valid medical reasons for these advanced bed "reservations." For instance, certain acutely sick surgical patients might have to be transferred to an ICU immediately following the completion of their procedure. In these cases, reserving a bed for the patient prior to completion of her procedure will ensure that the transfer can proceed immediately. However, in many other cases there is no apparent medical reason for the current method of assignment.

In a capacity constrained environment like MGH, premature bed assignments have the potential to cause patient delays that are unrelated to bed availability. This is illustrated in the following hypothetical example with two patients (an elective surgery patient and an ED patient), and two beds that become available at different times.

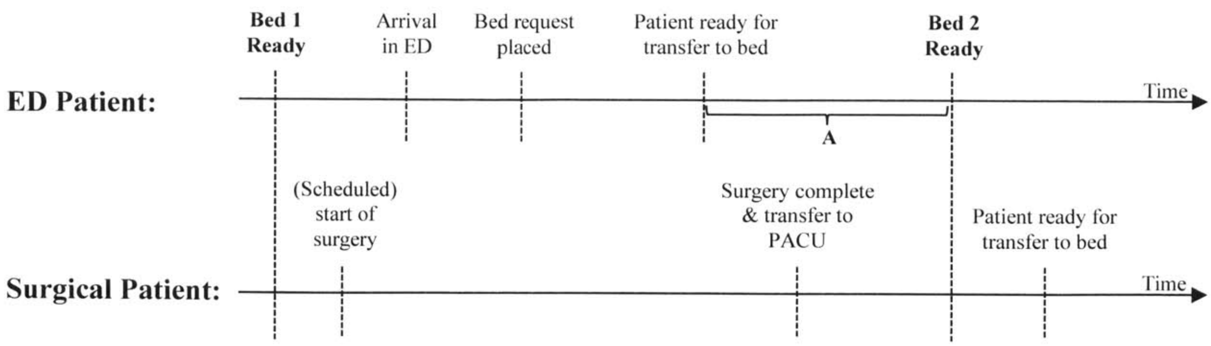


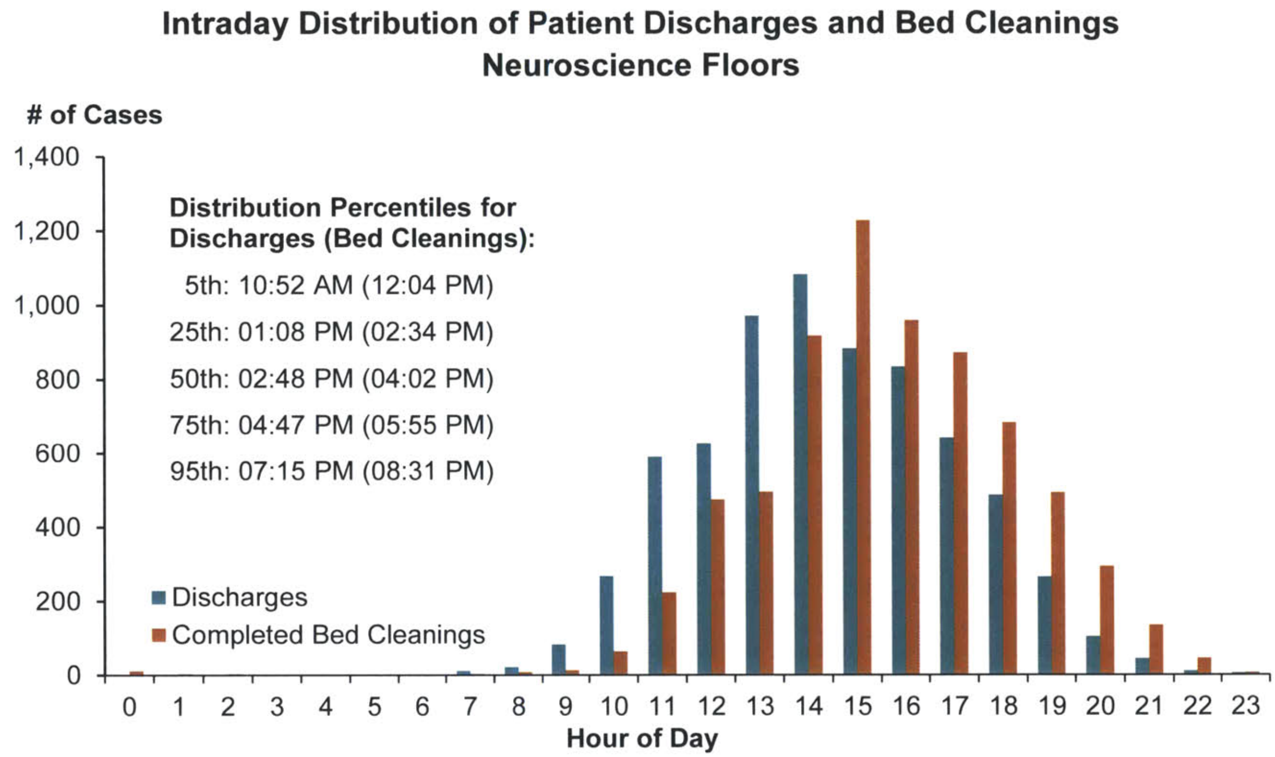
Figure 2 - Bed Wait Time Example

Following the guidelines discussed in Section 3.3.2, the surgical patient would be assigned to Bed 1 since the scheduled start of her surgery precedes both the arrival and the subsequent bed request of the ED patient. The ED patient would be assigned to Bed 2, requiring that patient to wait for A units of time until her bed is ready. Note that the wait could be avoided by holding off on the bed assignment of the surgical patient, and assigning Bed 1 to the ED patient instead. The change would cause no disadvantage to the surgical patient since she is not medically ready for transfer until after the second bed becomes available.

The distinction between bed wait hours that are unrelated to bed availability and bed wait hours that are imposed by capacity constraints is important because wait hours unrelated to bed availability can be reduced through process improvement and without increases in bed capacity. Capacity-imposed wait hours on the other hand cannot be eliminated without the creation of additional bed capacity (e.g., through earlier discharges).

3.4.2 Misalignment of Intraday Timing of Admissions and Discharges

The timing of discharges from the neuroscience units and the timing of admission requests to these units are currently not aligned, with discharges generally occurring later in the day. The misalignment of discharges and admissions has the potential to cause backlogs of patients waiting to be transferred to inpatient units in the perioperative environment, the ED, and other parts of the hospital. The congestion resulting from these backlogs causes delays and cancellations of surgeries, and affects the ED's ability to accept new patients. The alignment of discharges and admissions is therefore of crucial importance to quality of care, patient and care provider satisfaction, and hospital profitability.



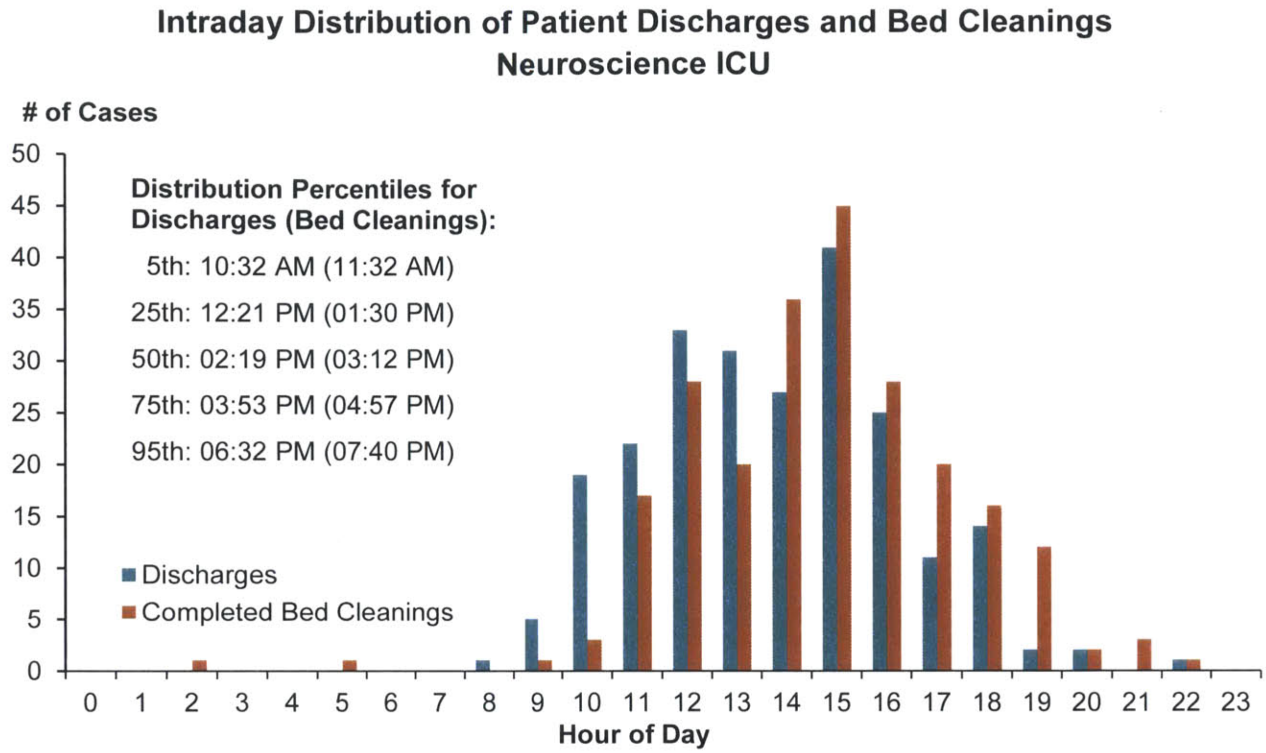
Sources: CBEDs, Patcom

Notes: Analysis based on all 6,938 patient discharges and associated bed cleanings that occurred on neuroscience floors (Lunder 7 and 8) between January 1, 2012 and June 30, 2013. Hospital-internal transfers (i.e., transfers from a neuroscience floor to another MGH location) and patient expirations are excluded.

Figure 3 - Intraday Distribution of Patient Discharges and Bed Cleanings on Neuroscience Floors

Figure 3 shows the time that floor patients leave their beds as well as the time their beds are cleaned and ready to receive the next patient. Figure 4 shows the same analysis for the neuroscience ICU.

As shown in these charts, discharges occur primarily in the afternoon with an average discharge time of 2:14 PM (2:56 PM in the ICU). Bed cleanings take additional time, causing beds to be ready for new patients at 3:10 PM on average (4:08 PM in the ICU).



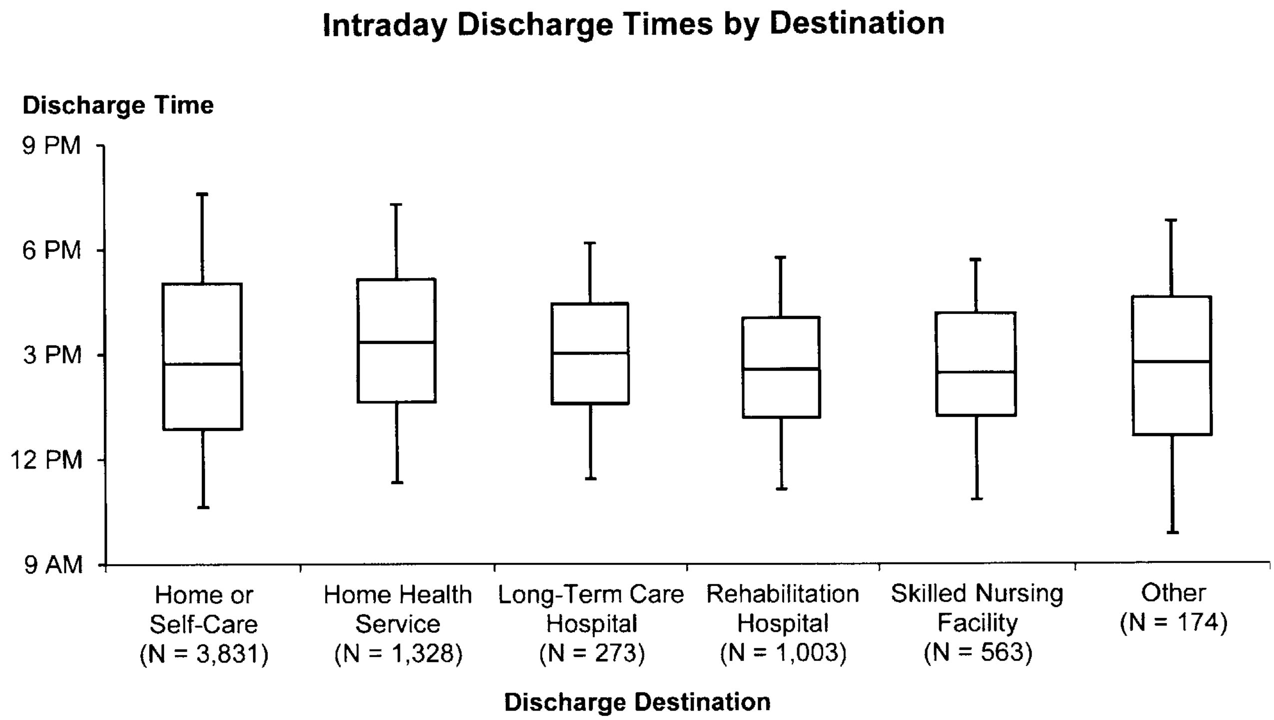
Sources: CBEDs, Patcom

Notes: Analysis based on all 234 patient discharges and associated bed cleanings that occurred in the neuroscience ICU (Lunder 6) between January 1, 2012 and June 30, 2013. Hospital-internal transfers (i.e., transfers from the neuroscience ICU to another MGH location) and patient expirations are excluded.

Figure 4 - Intraday Distribution of Patient Discharges and Bed Cleanings in Neuroscience ICU

In order to devise potential interventions that create better alignment, it is important to understand the causes of discharge delays. To this end, Figure 5 shows the discharge timing from both the ICU and the floors by discharge destination. It illustrates that no individual patient population is solely responsible for the intraday delays. Instead, patients seem to experience late discharges independent of their immediate post-MGH destination. It suggests that the intraday discharge timing is not primarily driven by capacity constraints at patients' destinations, but instead by internal processes that are under the control of MGH.[8] The finding is supported through interviews and observations at the hospital which indicated that current processes prioritize inpatient care and teaching activities over discharge processing during mornings.

[8] As shown in Figure 5, patients who are discharged to home (and therefore do not face capacity constraints at their destination) actually depart slightly later on average than patients who are transferred to rehabilitation hospitals and skilled nursing facilities. The median discharge times are 2:44 PM (home or self-care), 3:21 PM (home health services), 3:02 PM (long-term care hospitals), 2:33 PM (rehabilitation hospitals), 2:27 PM (skilled nursing facilities), and 2:44 PM (other), respectively.



Sources: Patcom

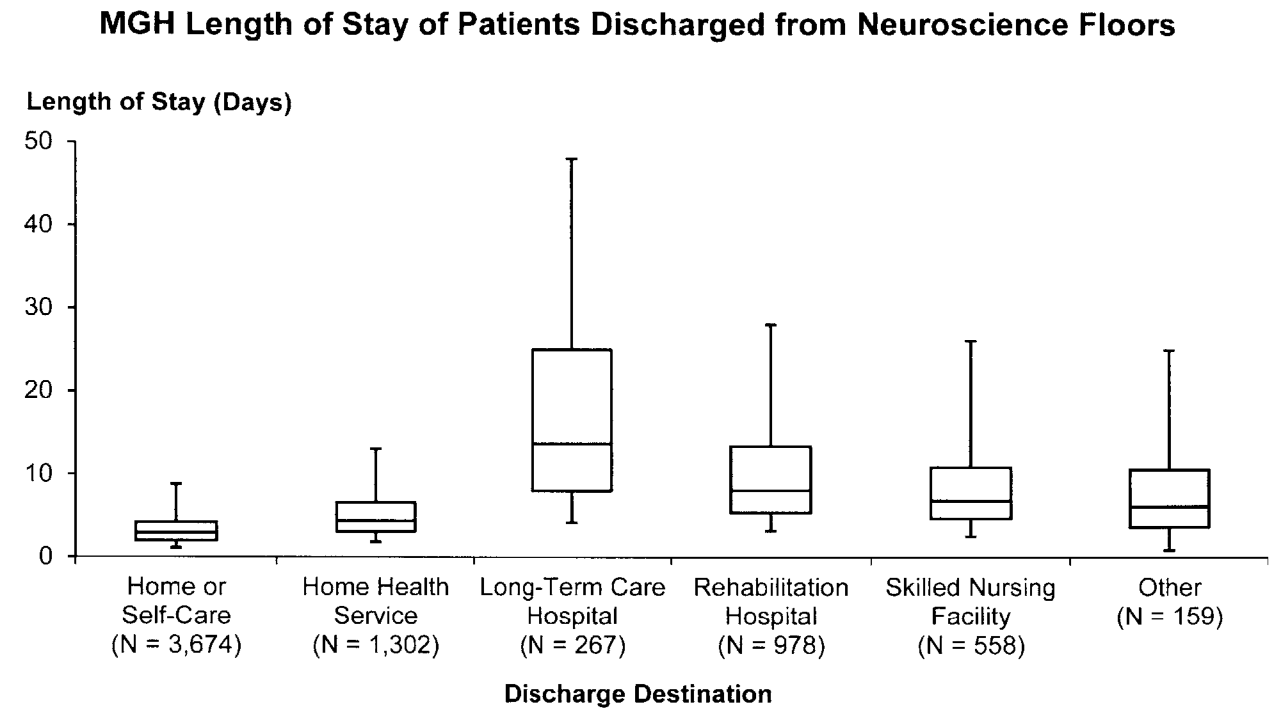
Notes: Analysis based on all 7,172 discharges from neuroscience units (Lunder 6, 7, and 8) between January 1, 2012 and June 30, 2013. Hospital-internal transfers (i.e., transfers from the neuroscience ICU to another MGH location) and patient expirations are excluded. Discharge destination "Other" includes: "Hospital Swing Bed," "Against Medical Advice," "Psych Hosp/Dist," "Hospice Home," "Other Type Facility," "Hospice," "Fed Hospital," "Short Term General Hospital," and "Law Enforcement." Upper and lower bounds correspond to 95th percentiles and 5th percentiles, respectively.

Figure 5 - Intraday Discharge Times by Destination

3.4.3 Extended Length of Stay for Patients Discharged to Other Care Facilities

In addition to intraday discharge delays, the current state analysis also indicated that patients who require continued professional care after discharge from MGH currently have significantly longer lengths of stay at the hospital. Figure 6 compares the length of stay for patients discharged from neuroscience floors to different destinations.[9] The chart clearly shows that patients discharged to professional care facilities spend much longer at MGH then patients discharged to self-care or home health services. While the effect is particularly severe for patients being discharged to long-term care (LTC) hospitals, patients going to rehabilitation hospitals or skilled nursing facilities also experience longer lengths of stay.

[9] A small number of patients (234) are discharged directly from the ICU. These patients are excluded from the analysis but they exhibit the same length of stay pattern. Between January 1, 2012 and June 30, 2013, 157 patients were discharged directly from the neuroscience ICU to home or self-care, 26 to home health services, 25 to rehabilitation hospitals, 6 to long-term care hospitals, 5 to skilled nursing facilities, and 15 to other destinations.



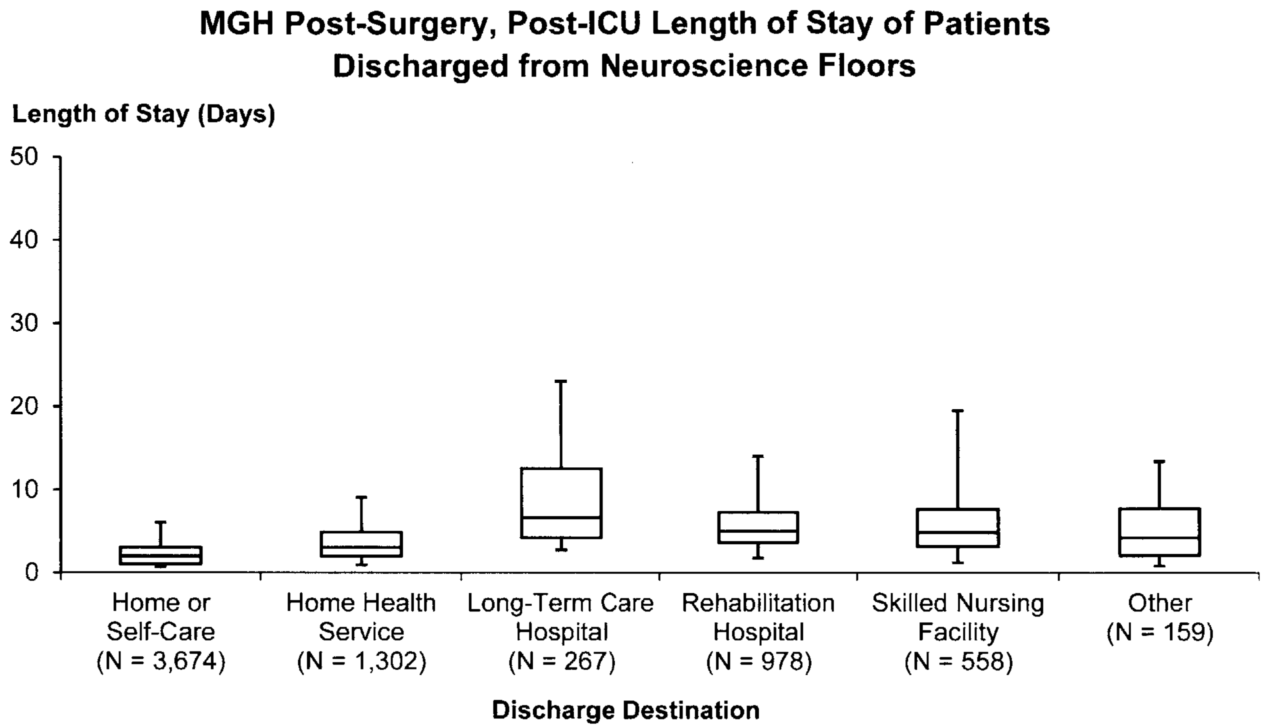
Sources: Patcom

Notes: Analysis based on all 6,938 discharges from neuroscience floors (Lunder 7 and 8) between January 1, 2012 and June 30, 2013. Hospital-internal transfers (i.e., transfers from a neuroscience floor to another MGH location) and patient expirations are excluded. Upper and lower bounds correspond to 95th percentiles and 5th percentiles, respectively.

Figure 6 - MGH Length of Stay of Patients Discharged from Neuroscience Floors to Different Destinations

While part of the increase in length of stay is appropriate due to clinical reasons (i.e., patients going to professional care facilities are sicker on average than patients going home), part of the increase in length of stay also seems to be due to post-MGH capacity constraints at the patients' intended destinations. This hypothesis is supported through interviews with attending nurses, case managers, and other care providers directly involved in the discharge process. According to these discussions, the capacity-imposed delays are particularly severe for patients who go to the highly capacity constrained rehabilitation facilities inside Partners' health care network. MGH currently discharges more than 24% of its patients with continued inpatient care needs to Partners' facilities.

In order to reduce variation in length of stay due to clinical reasons, we analyze the share of patients' total length of stay that occurs after completion of their last surgery or their last ICU-to-floor transfer, whichever is later. This analysis is shown in Figure 7. The chart supports the hypothesis that patients going to care facilities indeed face delays due to capacity constraints at their post-MGH destinations, as well as for other non-clinical reasons.



Sources: Patcom

Notes: Analysis based on all 6,938 discharges from neuroscience floors (Lunder 7 and 8) between January 1, 2012 and June 30, 2013. Hospital-internal transfers (i.e., transfers from a neuroscience floor to another MGH location) and patient expirations are excluded. Upper and lower bounds correspond to 95th percentiles and 5th percentiles, respectively.

Figure 7 - MGH Post-Surgery, Post-ICU Length of Stay of Patients Discharged from Neuroscience Floors to Different Destinations

4 Data-Driven Simulation of Current State Patient Flow and Potential Interventions

4.1 Introduction

This section discusses the data-driven model that is used to simulate the current state of neuroscience patient flow and to predict the impact of several potential interventions. The simulation is implemented using the SAS software suite and Promodel Corporation's MedModel modeling environment. It uses historical timestamps from a variety of data sources at MGH to create a comprehensive model of the neuroscience patient flow between September 2011 (opening of the Lunder building) and June 2013. The model tracks all inpatients who visited one of the neuroscience units (i.e., Lunder 6, 7, or 8) during this time and/or were cared for during (part of) their stay by the neurology or neurosurgery services. All other patient populations (including all outpatients) are not tracked explicitly. While these patient populations may cause capacity constraints in certain parts of the hospital, the neuroscience units constitute a relatively closed system. Outpatients and non-neuroscience inpatients therefore do not contribute significantly to capacity constraints in the neuroscience units.

Section 4.2 discusses the data sources used to build the simulation and the data preparation that was performed. Section 4.3 describes the modeling framework and the three major modules (i.e., the ED, the perioperative environment, and the inpatient bed units) that are part of the overall model. The discussion of each module includes an explanation of the relevant processes and queues, as well as the data used to simulate the module. Section 4.4 defines the performance metrics that are used to quantify the impact of the different tested interventions compared to the current state. Section 4.5 defines the three different interventions that are analyzed using this model (i.e., just-in-time bed assignments, discharges earlier in the day, and multi-day length of stay reductions).

4.2 Data Sources and Preparation

The simulation model uses data from a variety of sources at MGH, including the ED information system (ED internal patient flow), the perioperative case data (surgical patient flow), Patcom (hospital-wide patient flow and patient characteristics), and CBEDs (bed cleaning information). The historical timestamps recorded in these data sources are used to indicate the transitions of patients from one process or queue to another, and to determine the statuses of beds in the neuroscience units. The following sections provide brief descriptions of the different data sources, the specific variables that are used in the patient flow simulation, and the data cleaning process.

4.2.1 Emergency Department Information System (EDIS)

EDIS records all emergency room visits at MGH. The historical EDIS dataset contains the following relevant timestamps for each emergency room visit during the period of study:

Variable	Description
Arrival Time	*Date and time patient arrived in the ED*
Bed Request Time	*Date and time ED staff placed an electronic bed request for the patient* Bed requests are frequently made before a patient's ED treatment is complete and the timestamp is consequently considered a lower bound for a patient's readiness for transfer. (See Section 4.3.1 for details.)
Bed Assignment Time	*Date and time Admitting assigned a bed to the patient* The bed may be clean, in cleaning, dirty, or still occupied by another patient at the time of assignment.
Bed Assignment	*Identifier for the bed that the patient was assigned to* This information is populated at the bed assignment time. It is used to link the EDIS data with the CBEDS bed cleaning data.
Bed Clean Time	*Date and time patient's bed was cleaned and ready for occupancy*[10]
Physician Handoff Time	*Date and time attending physician in the ED informed the attending physician for the patient's impending medical service about the condition of the patient* The handoff timestamps are used as upper bounds for purposes of estimating patients' readiness for transfer. (See section 4.3.1 for details.)
Nurse Handoff Time	*Date and time patient's nurse in the ED informed the responsible nurse in the patient's destination inpatient unit about the condition of the patient*
ED Departure Time	*Date and time patient left the ED for the next destination (e.g., to go to an inpatient unit or the OR)*

Table 1 - EDIS Variables Used in Simulation

[10] The EDIS bed assignment time is strictly less than or equal to the EDIS bed clean time since EDIS only retrieves the bed status information from CBEDs after the bed assignment has been made. In cases where patients are assigned to beds that are already clean, the EDIS bed assignment time and EDIS bed clean time are equal. In these cases the true bed clean time, which precedes the bed assignment time, has to be determined by matching up the EDIS data with the CBEDs bed cleaning data using the bed identifier. The matching makes it possible to determine the actual time at which the bed became available. For purposes of this study, we use bed clean time to refer to the true (or CBEDs) bed clean time.

Data Preparation of EDIS Data

The EDIS record of each patient stops being updated after the patient departs the ED. For this reason, some timestamps are not recorded in cases where associated events happened after the patient's departure. In particular, a small number of patients who went from the ED to a neuroscience unit do not have a valid bed assignment time and/or bed clean time in the EDIS data. While this does not have a direct effect on the simulation, these observations (83 patients who went from the ED to Lunder 7 or 8, and 35 patients who went from the ED to Lunder 6) have to be excluded during model validation since no historical bed wait times can be calculated for these patients. See footnotes of tables in Appendix F for more details.

4.2.2 Perioperative Case Data

Variable	Description
Surgery Booking Time	*Date and time surgery was booked*
Arrival Time (Preop)	*Date and time patient arrived in a perioperative bay for preoperative procedures* Preoperative variables are not populated for patients who were transferred straight to the OR (e.g., emergent surgical patients from the ED).
Departure Time (Preop)	*Date and time patient departed the perioperative bay for the OR*
Arrival Time (OR)	*Date and time patient arrived in the OR*
Surgery Completion Time	*Date and time surgery was completed*
Departure Time (OR)	*Date and time patient left the OR*
Arrival Time (Postop)	*Date and time patient arrived in a perioperative bay for post-anesthesia care and recovery* Postoperative variables are not populated for patients who were transferred directly from the OR to an ICU or floor bed.
Patient Ready to Depart PACU Time	*Date and time patient was clinically ready to be transferred from the perioperative bay to a floor bed*
Departure Time (Postop)	*Date and time patient departed the perioperative bay for a hospital floor or ICU bed, or for discharge from the hospital*

Table 2 - Perioperative Variables Used in Simulation

This perioperative case data contain the perioperative patient flow information. It is organized by surgical case. Variables that are used in the simulation or for purposes of data validation are described in Table 2.

Data Preparation of Perioperative Case Data

While the perioperative data generally capture the surgical case flow accurately, the timely recording of the patient-ready-to-depart-PACU timestamp frequently does not occur. Out of 2,321 patients who went from the PACU to a neuroscience floor (Lunder 7 or 8) before June 30, 2013, the patient-ready-to-depart-PACU timestamp is recorded less than five minutes prior to patients' actual departures in 1,073 cases, implying that only about 50% of patients experienced delays.

Through interviews with relevant stakeholders and the observation of work processes in the PACUs at MGH, we know that this inference is not an accurate reflection of reality. The data error results from the fact that the perioperative staff frequently does not record patients' medical readiness for transfer in a timely fashion. Instead, the timestamp is often recorded along with the postoperative patient departure timestamp, when patients are checked out of their perioperative bay.

Hence, we sample the patient-ready-to-depart-PACU timestamp in cases where it is within five minutes of the postoperative departure timestamp from a triangular distribution. The distribution spans from the patient's postoperative arrival time to the postoperative departure time and peaks at the departure time.

4.2.3 Patcom Data

The Patcom data source covers patient flow for all admitted patients throughout the hospital, as well as several patient characteristics. The Patcom variables listed in Table 3 are used in the simulation. While all of these variables originate from Patcom, they were retrieved from several distinct MGH datasets, which are organized in different ways. Specifically, we use the Admission-Discharge-Transfer (ADT) dataset, the Data for Quality (D4Q) dataset, and the Morrisey Continuing Care Management (MCCM) dataset. The ADT and MCCM datasets are organized by patient-bed combination and record the historical patient flow between different beds and units of the hospital. These datasets allow us to track the movement of inpatients during their stay at MGH. The datasets are maintained by Admitting and Case Management, respectively. Meanwhile, the D4Q data are organized by hospital visit and provide patient and visit characteristics. The D4Q dataset is maintained by the hospital to track various quality measures. The source dataset for each variable is indicated under the description heading in Table 3.

Variable	Description
Admission Time	*Date and time patient was admitted to MGH* (ADT) The admission time precedes the first patient arrival time. For ED patients the admission time is recorded when the attending physician in the ED decides that the patient has to be admitted. For all other patient populations it is recorded approximately when the patient arrives at MGH or when the patient transfer to MGH (e.g., from another hospital) begins. Depending on the patient, the time between admission and bed arrival is consequently spent in the ED, the perioperative environment, another clinical location at MGH, or in transit.
Patient Arrival Time	*Date and time patient arrived in each bed visited during her hospital stay* (MCCM and ADT)
Patient Departure Time	*Date and time patient departed from each bed visited during her hospital stay* (MCCM and ADT) A patient's last bed departure time during an individual hospital visit is her discharge time (e.g., in Figure 3). For all hospital-internal transfers, the departure time is equal to the arrival time in the patient's next location (i.e., transit times between different inpatient locations are not captured).
Bed Identifier	*Identifier for each bed that the patient visited during her hospital stay* (MCCM and ADT)
Discharge Location	*Identifier of the location a patient was discharged to* (D4Q) See footnote of Figure 5 for more details.

Table 3 - Patcom Variables Used in Simulation

Data Preparation of Patcom Data

The Patcom data are cleaned and collapsed in a multi-stage process. First, the data have to be cleaned in order to remove observations that do not correspond to actual patient movements. These false patient movements exist because Patcom logs all data entries made by system users, including erroneous ones. Erroneous observations are identified and removed using several different criteria outlined below.

1) Comparison of the MCCM and ADT data: The MCCM and ADT datasets underwent different filtering and cleaning processes prior to our receipt of the datasets. A comparison of the two datasets can consequently reveal faulty observations. To give an example, if a patient moved from bed A to bed B, and then (soon afterwards) to bed C in one dataset, but the same patient moved directly from bed A to bed C in the other dataset, we assume that the latter is correct and that the patient never went to bed B.[11]
2) Comparison of the MCCM/ADT data with EDIS and perioperative data: We compare the Patcom patient flow data with the EDIS and perioperative data. In cases where the Patcom data indicate that the patient was in a certain inpatient bed, but the EDIS or perioperative data indicate that the patient was in the ED or perioperative environment at the same time, we assume that the latter is correct.
3) Removal of short patient stays: We also remove observations that are unlikely to correspond to real patient movements due to their length of stay. Specifically, if a patient went from bed A to bed B, and then to bed C less than an hour later, we assume that the patient went directly from bed A to bed C in reality. In these cases we assume that the patient stayed in bed A until their B-to-C transfer time in the raw data.

[11] In cases where patients spent a significant amount of time in location B, we evaluate the validity of observation B on a case-by-case basis. In general, we find that the MCCM dataset corresponds more closely to actual patient movements since these data were cleaned by case management prior to our receipt of the data.

After cleaning, the Patcom data for each patient are aggregated by inpatient unit. For purposes of the simulation, we distinguish between the following four groups of inpatient locations (in addition to the ED and the perioperative environment):

1) Neuroscience ICU (Lunder 6): This location includes all 22 beds in the Lunder 6 ICU.
2) Neuroscience Floors (Lunder 7 and 8): This location includes all 64 beds on the two Lunder neuroscience floors.
3) Overflow ICUs: This location includes all beds in MGH non-neuroscience ICUs.
4) Overflow Floors: This location includes all beds on MGH non-neuroscience floors.

The effect of the transformation is demonstrated in the following example for a hypothetical patient:

Original Data

Patient Bed	Time In	Time Out
Lunder 6 (ICU) Bed: 24A	2012/1/1 12:56 PM	2012/1/4 9:23 AM
Lunder 6 (ICU) Bed: 28A	2012/1/4 9:23 AM	2012/1/5 4:31 PM
Ellison 4 (ICU) Bed: 14A	2012/1/5 4:31 PM	2012/1/7 7:23 PM
Lunder 7 (Floor) Bed: 60A	2012/1/7 7:23 PM	2012/1/10 6:45 PM
Lunder 8 (Floor) Bed: 18A	2012/1/10 6:45 PM	2012/1/10 7:12 PM
Lunder 8 (Floor) Bed: 74A	2012/1/10 7:12 PM	2012/1/11 9:14 AM
White 11 (Floor) Bed: 34B	2012/1/11 9:14 AM	2012/1/12 3:35 PM
Gray 11 (Floor) Bed: 42A	2012/1/12 3:35 PM	2012/1/14 6:35 PM

Transformed Data

Patient Location	Time In	Time Out
Lunder 6 (ICU) Last bed: L06-24A	2012/1/1 12:56 PM	2012/1/5 4:31 PM
Overflow ICU Last bed: E04-14A	2012/1/5 4:31 PM	2012/1/7 7:23 PM
Lunder 7/8 (Floor) Last bed: L08-74A	2012/1/7 7:23 PM	2012/1/11 9:14 AM
Overflow Floor Last bed: G11-42A	2012/1/11 9:14 AM	2012/1/14 6:35 PM

Table 4 - Patcom Data Transformation Example

As seen in the table above, each transformed observation is associated with the last bed that the patient visited in that particular location group. This information is needed to match each observation with the bed cleaning that occurred after the patient's departure from that location.

As a result of the transformation, all patient movements within each of the four locations are ignored. The approach slightly reduces the number of bed cleanings that occur in the simulation relative to the historical data, creating slightly more bed capacity than existed in reality.[12] However, we find that this effect is small since only about 5% of patient movements are internal to one of the four groups of locations. Furthermore, intra-location patient transfers tend to occur when spare bed capacity is available and the effect on patient wait times is minimal.

4.2.4 CBEDs Bed Cleaning Data

The bed cleaning data originate from the MGH bed management system CBEDs. The dataset is organized by bed cleaning and contains the following variables that are used in the simulation.

Variable	Description
Bed Identifier	*Identifier of the bed that was cleaned* The bed identifier and bed dirty time are used to match up the CBEDs data with the Patcom patient flow data.
Bed Dirty Time	*Date and time patient left the bed and the bed status changed from occupied to dirty, generating a request for cleaning* This variable corresponds closely to the bed departure time (see Table 3) and is used to match the bed cleanings to the correct patient transfers.
Bed In Progress Time	*Date and time bed cleaning was started*
Bed Clean Time	*Date and time bed cleaning was completed and the bed was ready for the next patient* The bed clean time is fed electronically to EDIS for beds that are assigned to patients in the ED (see Table 1).

Table 5 - CBEDs Variables Used in Simulation

[12] To visualize this effect, consider a patient being transferred from bed A to bed B in the same unit. After the transfer, bed A has to be cleaned for two hours. During the cleaning time the patient effectively takes up two beds worth of capacity. In the simulation this transfer and the associated bed cleaning do not occur and we consequently see an increase in capacity by two bed-hours.

Data Preparation of CBEDs Bed Cleaning Data

A significant number of timestamps are missing in the bed cleaning data. Out of 13,574 bed cleanings that were logged on Lunder 6, 7, or 8 before July 1, 2013, a total of 5,184 are missing one or more of the three timestamps listed in Table 5. Of these 5,184 observations, 1,223 are missing the bed clean time.

In order to determine when a particular cleaning was completed, and to match the cleaning data with the Patcom data, we require at least a valid bed clean time for each observation. The missing bed clean times are consequently generated using a multi-stage sampling process, as outlined below:

1) Calculate the distribution of bed cleaning durations (i.e., duration from bed in progress time until bed clean time) from observations that have both of these timestamps (11,735).
2) Generate bed clean times for observations with valid bed in progress times and missing bed clean times (495 out of 1,223). This is done by sampling a cleaning duration from the distribution generated in the previous step and adding it to the bed in progress time.
3) Calculate the distribution of bed turnover durations (i.e., duration from bed dirty time until bed clean time) from observations that have both of these timestamps (8,834).
4) Complete the bed clean time for the remaining observations that have neither a bed clean time nor a bed in progress time (728 out of 1,223). This is done by sampling a turnover duration from the distribution generated in the previous step and adding the duration to the bed dirty time.

While the numbers above are aggregates for all three neuroscience units, the process is carried out separately for ICU and floor beds to account for the differences in cleaning processes between these two types of beds.

Even after completing the bed clean times through sampling, not all patient transfers originating in the neurosciences can be matched to bed cleanings. This problem is likely due to missing observations in the bed cleaning data. We find that 564 out of 12,649 patient transfers that originate in a neuroscience unit cannot be matched to bed cleanings that occurred within 24 hours of the transfer. For these cases, the bed clean time is calculated by sampling a turnover duration from the distribution generated in step (3) above and adding it to the Patcom patient departure time.

4.3 Modeling Framework

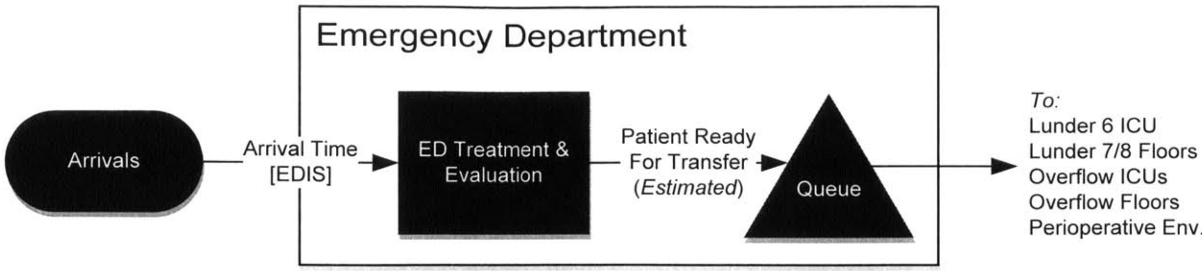
The patient flow model consists of three interconnected modules (the ED, the perioperative environment, and the inpatient bed units), which are described separately in this section. The patient flow is determined using the historical timestamps from the data sources described in Section 4.2. As discussed below, we measure the time that patients spend in different queues in the system and use this information to compare the effectiveness of the current state simulation and the different interventions. While patients' lengths of stay in different processes and queues change as a result of the interventions, the routing of patients (i.e., the locations visited by patients, and the order in which they visited these locations) is not modified in either the current state simulation or the interventions. It corresponds exactly to patients' journeys through the various units of the hospital during their actual visits.

Several major challenges had to be addressed in the design of the model. First, the times at which patients are medically ready for transfer between two different locations at MGH had to be estimated. These timestamps are not recorded directly except in the perioperative environment. The estimation of these timestamps is important in order to ensure that the current state model reflects the historical patient flow accurately. The same estimated timestamp is used in the current state model and the intervention models.

Second, the current bed assignment policies had to be modeled. This process was difficult because the process is currently not standardized and no transparent guidelines exist on how to prioritize assignments. Solutions that we developed to address these modeling challenges are explained in the following sections.

4.3.1 Emergency Department

The model of the MGH ED is shown in Figure 8. ED patients initially arrive in the ED. They are then evaluated, diagnosed, and treated accordingly. During this process, a bed is requested for patients who need to be admitted and a surgery time is booked for patients who will go straight from the ED to the OR.



Notes: Processes are indicated using rectangles, queues are indicated using triangles. Transitions between different processes and queues are determined based on timestamps in the historical data. The appropriate timestamps are shown along the connecting arrows. The data sources for these timestamps are indicated in square brackets. Timestamp estimates are italicized.

Figure 8 – Model of the Emergency Department

After the ED evaluation and treatment process is completed, patients wait to be transferred to their next destination, which can either be a hospital bed in a neuroscience or "overflow" unit, or the perioperative environment. While Figure 8 shows only a single queue, logically there are multiple queues, one for each post-ED destination.[13]

Modeling ED Processes and Queues Based on Timestamps

The duration of the evaluation and treatment process is determined using a variety of historical timestamps. The process starts when patients arrive in the emergency department and their arrival timestamp is recorded in the data.

The evaluation and treatment process is complete when patients are medically ready to be transferred to their next destination inside the hospital. Since this time is not recorded directly in the available data, the medical readiness of patients has to be estimated. The estimation approach varies depending on the next destination of the patient.

The medical readiness of patients who went from the ED to an inpatient unit is sampled from a uniform distribution between the bed request time in EDIS and the first handoff timestamp in EDIS. Based on conversation with clinical staff, we determined that all patients should be medically ready to depart the

[13] This convention is also used in model diagrams in the following sections. The queue triangles can be thought of as patients waiting in a particular location. However, patients going to different destinations are tracked in separate queues in the implementation of the model since these patients do not compete for the same resources.

ED within twelve hours of their arrival. Hence, this is set as an upper limit for patients' readiness for transfer. Patients who were transferred from the ED to the perioperative environment are considered medically ready for transfer once their surgery is booked in the OR schedule. The exact calculation approach is summarized in Appendix D, Table 14.

Calculation of Wait Times in the ED

This section explains the technical details of how wait times are calculated in the patient flow model. We first address patients who are transferred to neuroscience units and then discuss patients who are transferred to other departments.

ED-to-Lunder 6 and ED-to-Lunder 7/8 Transfers

The wait times for patients who are transferred from the ED to a neuroscience unit are a key performance measure that is used to test the effectiveness of different bed management approaches. We distinguish between two types of wait times. First, the bed wait measures the time it takes for the bed to be cleaned (following the departure of the previous patient) and assigned.

Second, the transfer processing wait measures the remaining wait time in the ED after the bed has been cleaned and assigned. Among other things, this transfer processing time includes the time it takes to complete any physician and/or nursing handoffs that have not yet occurred, and the time needed to find an available transporter for the patient. After transfer processing is completed, the patient departs the ED and physically travels from the ED to her inpatient bed.

This sequence of events is shown in Figure 9. We distinguish between two different scenarios. In the first scenario, the patient experiences a bed wait because the bed has not been cleaned and assigned by the time the patient is medically ready for transfer. In the second scenario, the bed is cleaned and assigned before the patient is ready. Therefore, the patient does not experience a bed wait in the second scenario.

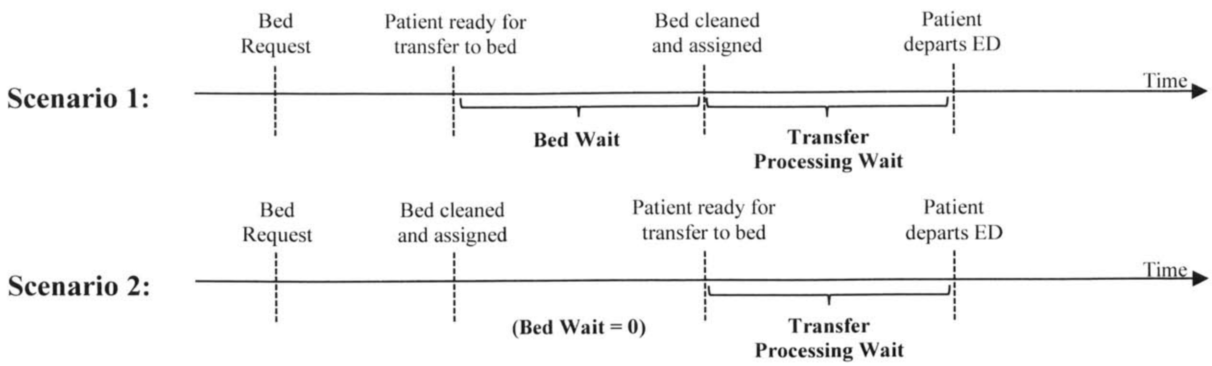
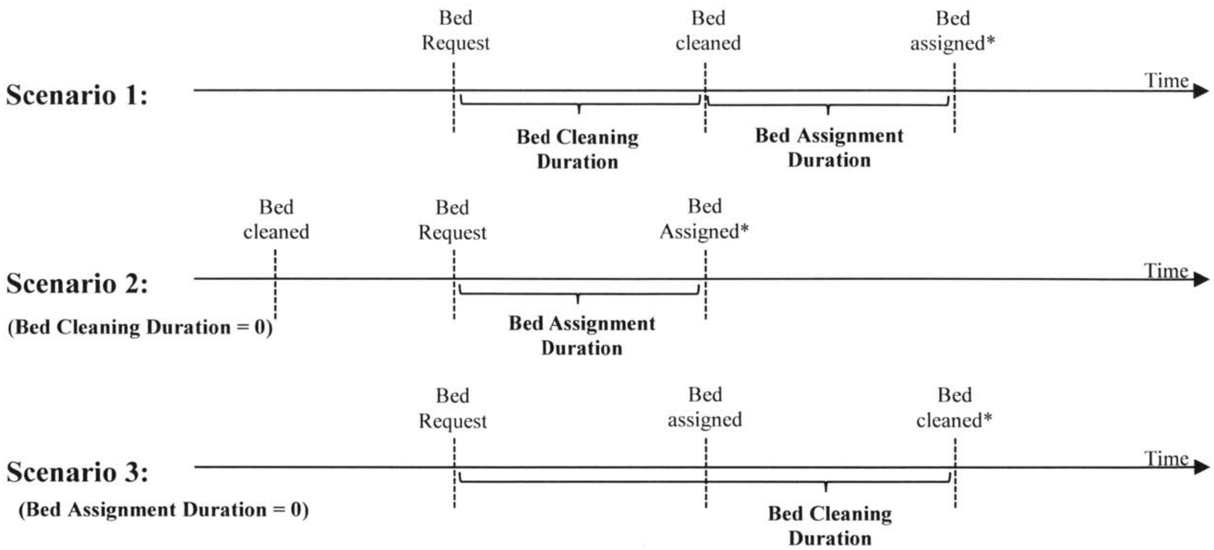


Figure 9 - Wait Time Illustration for ED-to-Lunder 6 and ED-to-Lunder 7/8 Patients

Transfer processing on the other hand does not start until the bed is cleaned and assigned, and the patient is medically ready. Therefore, patients experience transfers waits in both scenarios. Since the length of the transfer processing wait is not directly related to bed management practices, we assume that this component of the total wait does not change as a result of operational interventions. Since shorter patient wait times for beds may also speed up transfer processing, this is a conservative assumption. The duration of the transfer wait for each patient is calculated directly from the EDIS data and held constant in all modeled scenarios.

On the other hand, the length of the bed wait is directly affected by bed management practices. This is the component of the total wait that we aim to reduce through appropriate interventions. This part of the total wait ends when the bed is both cleaned and assigned.

The bed cleaning and bed assignment can happen in different orders, as shown in Figure 10. In the first scenario, the bed request, the bed cleaning, and the bed assignment occur in series. The bed cleaning has not been completed by the time Admitting receives the bed request from the ED. After the bed is cleaned, additional time passes until Admitting assigns the bed to the patient. In this case, both the bed cleaning and the bed assignment affect how soon the bed is "cleaned and assigned" (i.e., both the bed cleaning duration and the bed assignment duration are positive) after the bed request.



Notes: As defined above, the bed cleaning duration measures the time period from when the bed is requested until the bed is cleaned. If the bed is cleaned before the bed is requested, the bed cleaning duration is zero. The bed assignment duration measures the time from when the bed is requested or the bed is cleaned, whichever is later, until the bed is assigned. If the bed is assigned before it is cleaned, the bed assignment duration is zero. The time marked with an asterisk in each scenario corresponds to the "bed cleaned and assigned" time in Figure 9.

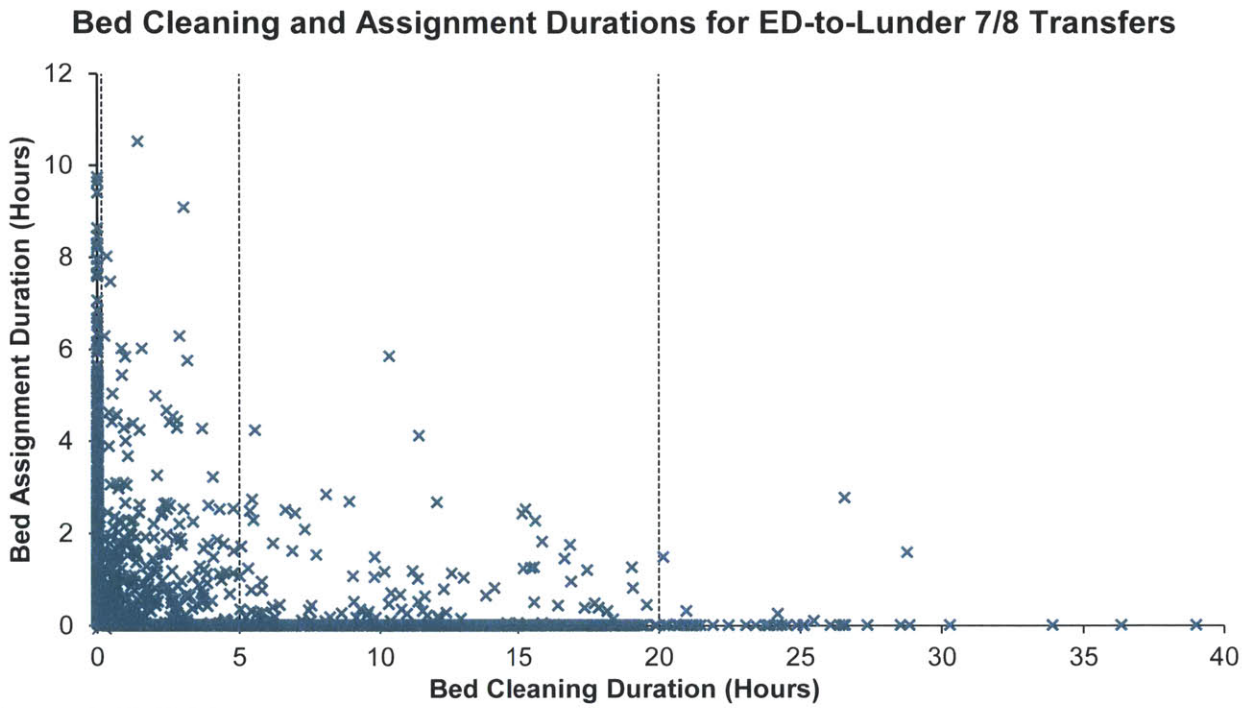
Figure 10 - Illustration of Bed Cleaning and Assignment Durations (ED)

In the second scenario, the bed cleaning is completed prior to the bed request. This represents the situation where the bed is clean and unoccupied at the time of the bed request. In this case, the bed cleaning is not a relevant factor (i.e., the bed cleaning duration is zero) and the bed assignment duration is measured from the bed request time instead of the bed clean time.

In the third scenario, the bed is assigned before it is cleaned. This scenario can occur because bed managers have the ability to assign patients to beds that are not yet ready for occupancy (either because the previous patient has not yet left the bed or because the bed cleaning has not yet been completed).[14] In this scenario the bed assignment process is not the limiting factor (i.e., the bed assignment duration is zero while the bed cleaning duration is positive).

[14] Note that while the bed assignment can be completed before the bed is cleaned, the bed assignment time can never precede the bed request (unlike the bed clean time) because Admitting, the department responsible for making bed assignments, is generally unaware of ED patients in need of beds until the bed request.

We consequently need to calculate a bed cleaning duration and bed assignment duration for every patient who went from the ED to a neuroscience unit. This information will then allow us to infer the bed wait time of the patient. The bed cleaning duration is a function of patient departures from the neuroscience unit that the ED patient is looking to transfer to (i.e., a bed has to open up), as well as assignment prioritizations made by Admitting (i.e., Admitting has to decide how to allocate available beds to waiting patients). The specific algorithm used to calculate the bed cleaning duration of each patient waiting to transfer from the ED to a neuroscience unit is described in Appendix A.

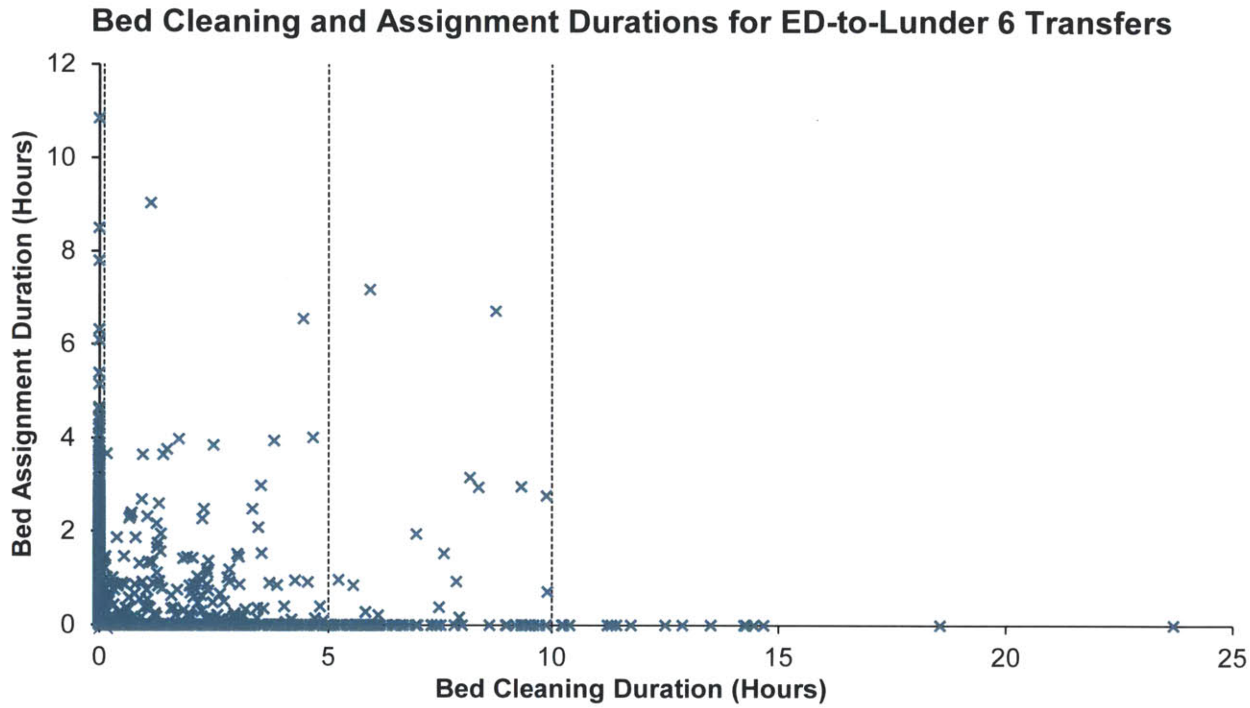


Sources: EDIS, CBEDs

Notes: Analysis based on 2,783 patients who were transferred from the ED to a bed on Lunder 7 or 8 before July 1, 2013. Patients without a valid bed request time, bed assignment time, or bed clean time in the historical data are excluded.

Figure 11 - Chart of Bed Cleaning and Assignment Durations for ED-to-Lunder 7/8 Transfers

After calculating bed cleaning durations, bed assignment durations have to be calculated in order to determine the point in time at which the bed was cleaned and assigned in Figure 9. While bed assignment duration can be calculated directly from the EDIS data, this is not appropriate because the historical data suggest that the bed cleaning durations and the bed assignment durations are strongly correlated.[15] For this reason, it is not accurate to assume that the bed assignment times would remain constant despite changes to bed cleaning times (e.g., as the result of one of the modeled interventions). The correlation between these two variables in the historical data is shown in Figure 11 and Figure 12.



Sources: EDIS, CBEDs

Notes: Analysis based on 1,138 patients who were transferred from the ED to a bed on Lunder 6 before July 1, 2013. Patients without a valid bed request time, bed assignment time, or bed clean time in the historical data are excluded.

Figure 12 - Chart of Bed Cleaning and Assignment Durations for ED-to-Lunder 6 Transfers

As shown above, bed assignment durations are significantly shorter for patients who experienced long bed cleaning durations. This relationship can be understood intuitively. Consider first the situation where no bed is available in an appropriate neuroscience unit at the time a patient's bed request is placed. This patient consequently has to wait for another patient to depart a bed and for that bed to be cleaned. Both of these processes are captured in the bed cleaning duration. Admitting, however, is already aware of the ED patient during the cleaning duration, and when the bed manager finally learns that an appropriate bed is

---

[15] The historical bed assignment duration can be calculated from the EDIS data as follows:
`Bed Assignment Duration = max(0, Bed Assignment Time - max(Bed Clean Time, Bed Request Time)).`

going to open up, she can assign the bed to the waiting patient even before the cleaning is completed. Therefore, the chance that a patient with a long bed cleaning duration will experience a short bed assignment duration (or none at all) is high.

On the other hand, if the ED patient's bed was already clean at the time of the bed request, the outcome changes. In this scenario Admitting does not have the opportunity to assign the bed before it is cleaned since the bed manager is not aware of the ED patient until the bed request is placed. Furthermore, Admitting is more likely to hold the bed for a period of time since it is known that the bed request was only placed recently and the patient may not be medically ready for transfer yet.[16] Hence, patients who experience short bed cleaning durations are likely to experience longer bed assignment durations. Of the 3,992 patients who were transferred from the ED directly to a neuroscience unit between January 1, 2012 and June 30, 2013, a total of 1,868 patients (48%) fall into this category. The beds of the remaining 2,054 patients (52%) were not yet clean when their bed requests were placed.

In order to capture this effect in the simulation, we sample the bed assignment durations for ED-to-Lunder 7/8 transfer patients from different distributions depending on the bed cleaning duration. Specifically, we divide the bed cleaning durations in Figure 10 into four groups (0 hours, >0 to 5 hours, >5 to 20 hours, and >20 hours) as indicated by the vertical lines. The bed assignment duration of each patient is then sampled from the available values in the bucket corresponding to the patient's bed cleaning duration. An equivalent process is followed for patients transferring from the ED to Lunder 6, except that the boundaries are set differently (0 hours, >0 to 5 hours, >5 to 10 hours, and >10 hours) to reflect the thresholds observed in Figure 12.

The final step in the calculation of wait times for ED-to-Lunder 7/8 and ED-to-Lunder 6 patients is the estimation of the transfer processing wait in Figure 9. This quantity can be calculated directly for each

[16] Beds may be held (despite outstanding bed requests) in order to maintain a capacity buffer that enables Admitting to respond faster in case a patient with a greater need for immediate bed placement arrives at the hospital.

patient from the EDIS data.[17] The transfer processing duration is held constant in all simulated scenarios and added to the patient's bed wait.

Patients Headed to Other Destinations at the Hospital

The total ED wait (including the transfer processing wait) for patients who were transferred from the ED to the perioperative environment or to an "overflow" inpatient unit is calculated as the difference between the patient's ED departure time and the estimated patient ready time. See Appendix D, Table 14 for the calculation of the latter. This duration is held constant in all simulated scenarios. Since the wait times for these patients do not change, they are not used to analyze the effectiveness of each scenario.

4.3.2 Perioperative Environment

A model of the MGH perioperative environment is shown in Figure 13.

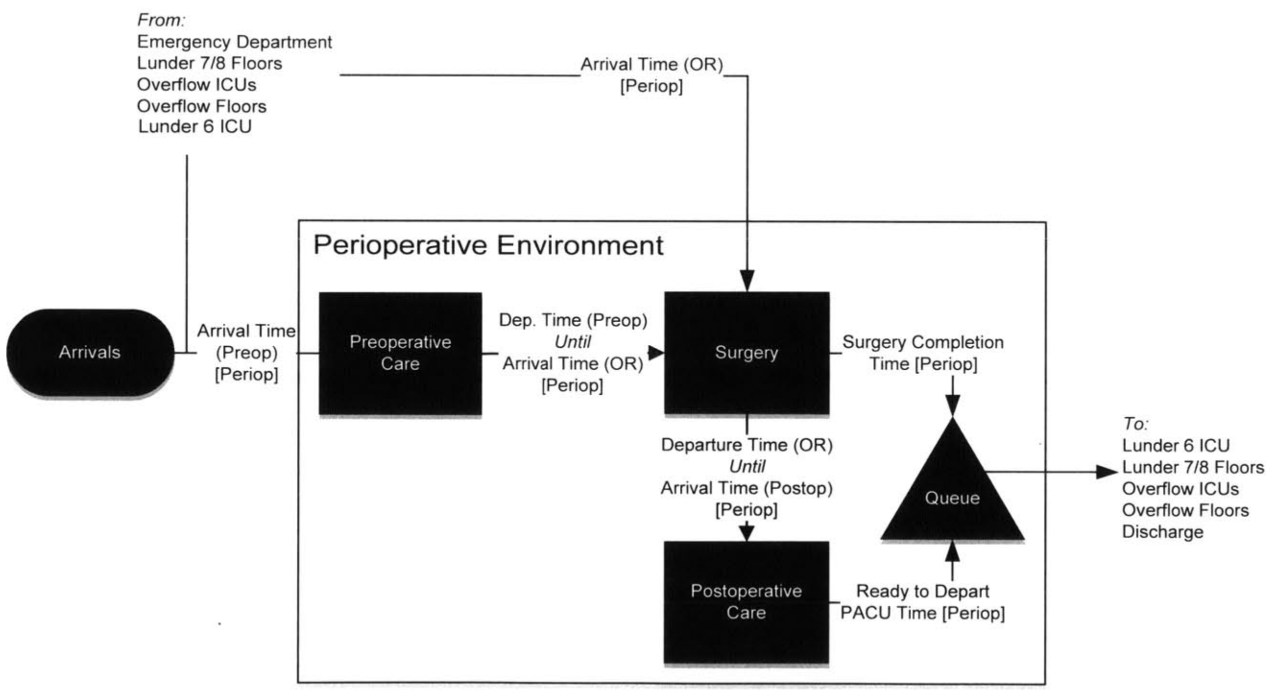


Figure 13 – Model of the Perioperative Environment

---

[17] The transfer processing wait is calculated as follows:
`Transfer Processing Wait = ED Departure Time - max(Patient Ready Time, Bed Assignment Time, Bed Clean Time).`

The perioperative environment receives patients from both internal and external sources. In addition to elective surgery patients who are admitted to the hospital through the perioperative environment, patients also come from the ED, and the different inpatient floors and ICUs at MGH. Critical patients (e.g., emergent cases from the ED) are brought directly to the OR while scheduled surgical patients are first brought to a perioperative bay in order to complete their work-up. After the preoperative preparations are complete, the latter category of patients is transferred to the OR for surgery.

After surgery, patients who do not require ICU-level care are generally transferred to another perioperative bay (also called post-anesthesia care unit, or PACU).[18] Here, these patients wake up and are prepared for transfer to an inpatient bed. After immediate post-surgical care and recovery are complete, these patients wait for transfer to their next destination. Meanwhile, patients with critical care needs are ideally transferred directly from the OR an ICU bed. If their bed is not ready at the end of surgery, these patients either stay in the OR until they can be transferred, or they are brought to a PACU.[19]

Modeling Perioperative Processes and Queues Based on Timestamps

The paths of patients through the perioperative environment, as well as the durations of the different processes and queues, are determined using a variety of historical timestamps. It is first determined whether a patient went through the preoperative process or went directly into the OR. The routing is implied by the existence (or lack thereof) of preoperative timestamps in the case data (see Table 2).

Patients who completed their surgical work-up in a perioperative bay enter the perioperative environment at their historical preop arrival time. These patients leave the preoperative care process for the OR at their

[18] Note that while many perioperative bays at MGH are used for both preoperative and postoperative care, the model in Figure 13 distinguishes between these two processes. The perioperative bays used for post-anesthesia care are collectively referred to as post-anesthesia care units ("PACU"). We use the latter term to refer specifically to the perioperative recovery process in Figure 13. The term "PACU patient" is used to describe patients who returned to a perioperative bay post-surgery.

[19] Exceptions to this rule exist. Some non-critical patients are also transferred directly from the OR to a floor bed.

historical preop departure time. They subsequently enter the surgical process in Figure 13 at their historical OR arrival time.[20]

The completion of the surgery process depends on the historical routing of patients. Patients who were transferred from the perioperative environment to an ICU, and patients who went directly from the OR to a floor bed, complete the surgical process at the historical surgery completion time.[21] These patients directly enter the transfer queue in Figure 13. The situation is different for patients who were transferred from the OR to a PACU, and then to a floor bed.[22] These patients depart the surgical process at the OR departure time and enter the PACU process at the postop arrival time. These patients transition from the postoperative care process to the queue at the patient-ready-to-depart-PACU time.

Patients consequently enter the queue when they are medically ready for transfer to an ICU or floor bed. The timestamps used to make this determination are summarized in Appendix D, Table 15.

Calculation of Wait Times in the Perioperative Environment

This section discusses the technical details of how patient wait times are calculated in the perioperative environment. We first address patients transferring to neuroscience units, and then discuss patients transferring to other departments.

Periop-to-Lunder 6 and Periop-to-Lunder 7/8 Transfers

The wait times for patients who were transferred from the perioperative environment to one of the neuroscience units are used as a performance metric for the different modeled scenarios (in addition to wait times for ED patients who made this transfer). Patients start to wait when they are medically ready

---

[20] Patients are considered in-transit between their preoperative departure time and their OR arrival time. This also applies to other patients who exit a process before their historical arrival in the next process. For example, if the historical data indicate that a patient left the ED (based on her ED departure time) 30 minutes before her preoperative arrival time, then this patient is considered to be in-transit for 30 minutes in the model.

[21] Note that this includes patients who went to a PACU prior to their transfer to an ICU bed. However, since these patients are medically ready for transfer to the ICU immediately following their procedure, they do not go through the PACU recovery process in the model.

[22] Similar to the preoperative care process, the existence (or lack) of postoperative timestamps in the case data (Table 2) is used to determine whether or not a patient was transferred to a PACU after surgery.

for transfer. The length of the wait depends on both availability of beds and the amount of time needed for transfer processing in the perioperative environment. This distinction is illustrated in Figure 14.

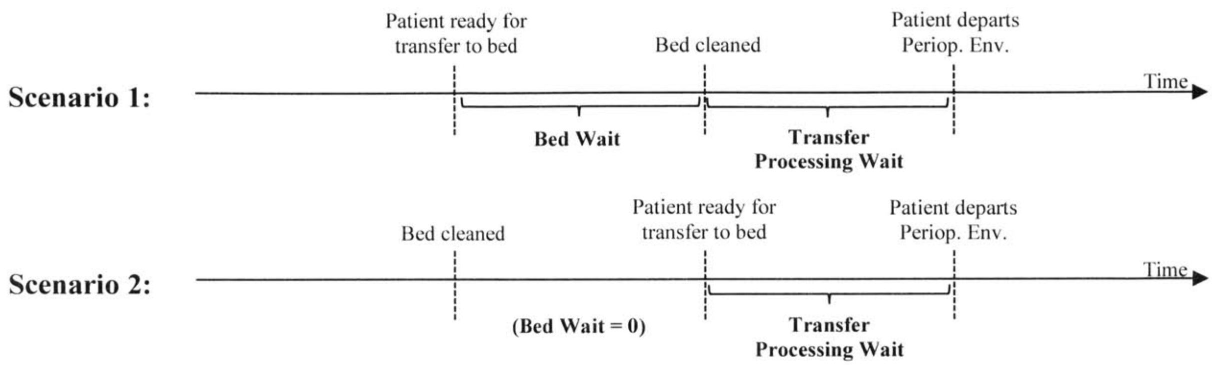


Figure 14 - Wait Time Illustration for Periop-to-Lunder 6 and Periop-to-Lunder 7/8 Patients

Note that these wait time calculations are essentially the same as in the ED except that bed assignments delays for perioperative patients are not modeled. Hence, the bed wait for perioperative patients measures the time from when patients are medically ready for transfer until their beds are cleaned. This duration is once again calculated using the algorithm described in Appendix A.

All patients transferring to an ICU, independent of whether or not they spent time in a PACU after surgery, are considered medically ready for transfer immediately after surgery. This assumption reflects the fact that ICU patients are generally only accommodated in PACUs due to capacity constraints, and not due to medical reasons. For floor patients on the other hand, the medical readiness for transfer depends on whether or not the patient visited a PACU post-surgery. Patients who went directly from the OR to a hospital floor are considered medically ready for transfer at the end of their surgeries. The readiness of floor patients who visited a PACU is inferred from the patient-ready-to-depart-PACU timestamp.

Bed assignment times are not recorded for perioperative patients. Thus, bed assignment durations cannot be calculated in the same way as in the ED. Ignoring bed assignment delays is equivalent to assuming that bed assignments are always made before patients' beds are cleaned or patients are medically ready for transfer, whichever is later.

While this is not a perfect assumption, we found that Admitting does generally attempt to assign elective (and sometimes non-elective) surgical patients to beds as early as possible. Since these patients are known to Admitting long before they are medically ready for transfer, bed assignments do happen before the bed is cleaned or the patient is ready in a large number of cases.[23] Hence, disregarding bed assignment delays does not have a significant impact on the model's ability to accurately reflect the current state. See Section 5.1 for more details.

After a patient's bed is ready, arrangements for transferring the patient from the perioperative environment to the appropriate neuroscience unit (Lunder 6, 7, or 8) have to be finalized. This transfer processing time includes the time it takes to check the patient out of the PACU or OR, and the time needed to find an available transporter for the patient. After transfer processing is completed, patients are brought from the perioperative environment to their inpatient beds.

The length of the transfer processing waits can only be calculated directly from the historical data for patients who returned from the perioperative environment to the same bed they occupied prior to surgery (since these are the only patients we know with certainty experienced no bed assignment delays). We use these patients to estimate the distribution of transfer processing times for all patients.[24,25]

---

[23] Bed managers learn about scheduled surgical admissions through the daily OR schedule, which is printed at the beginning of the day. Information about unscheduled surgeries of patients coming from the ED is relayed to bed managers through the ED bed request. Bed managers are consequently aware of surgical patients' bed needs before the surgery has even started in most cases.

[24] This process is carried out separately for OR-to-ICU, PACU-to-ICU, OR-to-floor, and PACU-to-floor transfers to account for systematic differences between the transfer processing times of these patient populations.

[25] While transfer processing times for ED and surgical patients are incorporated in the simulation, it is important to note that the accuracy of these processing waits has no effect on simulation results. Transfer processing times are excluded in the comparison of wait times between the different scenarios since they are unaffected by the modeled interventions.

The situation is different for patients waiting to transfer between different neuroscience units (i.e., Lunder 6-to-Lunder 7/8 and vice versa). The transfer processing times of these patients affect the bed wait times for other patients. For example, the transfer processing time of a patient waiting to transfer from Lunder 6 to Lunder 7/8 affects the bed wait time of patients waiting to transfer to Lunder 6 since the Lunder 6-to-Lunder 7/8 patient is still occupying her Lunder 6 bed during the transfer processing wait. This logic does not apply to patients waiting in the PACU, however, since the PACU is not explicitly capacity constrained in the model.

Patients Headed to Other Destinations at the Hospital

For patients who were transferred from the perioperative environment to an "overflow" inpatient unit, the total wait (including the transfer processing wait) is calculated by taking the difference between the OR departure time (for patients who did not transfer via the PACU) or the postop departure time, and the patient ready time (see Appendix D, Table 15 for the calculation of the latter). Patients' wait times are held constant in all simulated scenarios and not used to compare the effects of different bed management approaches.

4.3.3 Inpatient Units

Models of the neuroscience ICU and floors, and the overflow ICUs and floors at MGH are shown in Figure 15 and Figure 16, respectively.

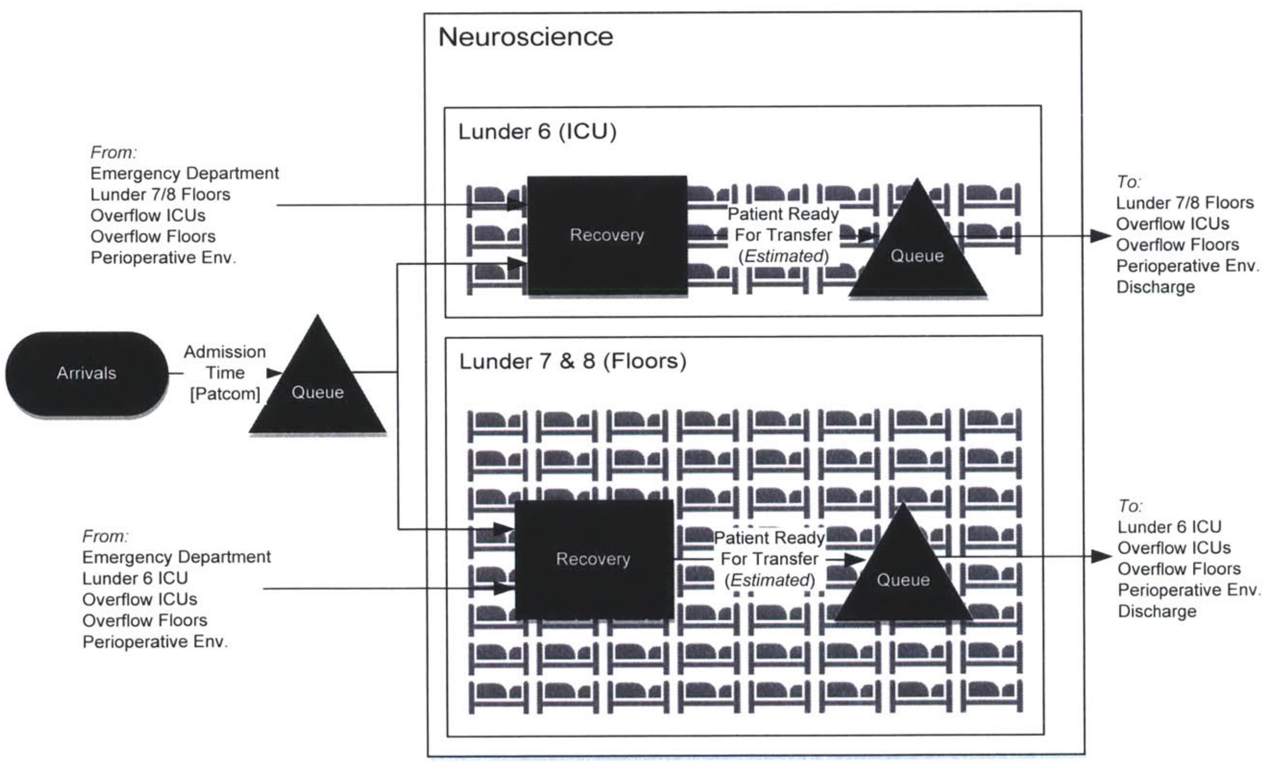


Figure 15 – Model of the Neuroscience ICU and Floors

The inpatient units receive patients from both the ED and the perioperative environment. In addition, patients are occasionally admitted directly to these inpatient units from outside the hospital. Patients are considered to be in recovery until they are medically ready for transfer to another location at MGH, or for discharge from the hospital.

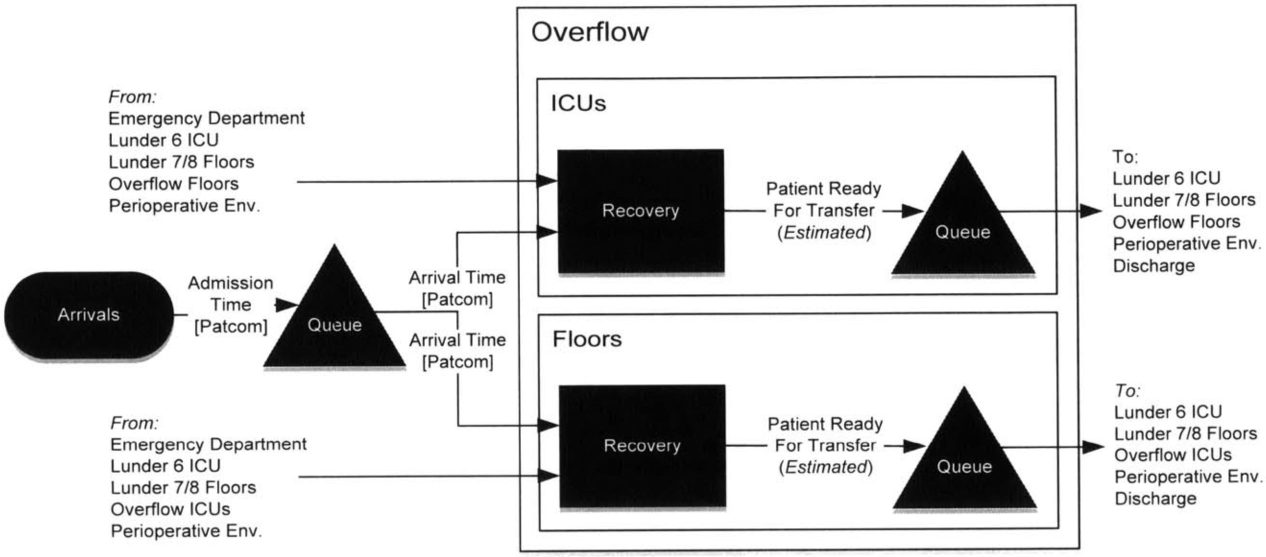


Figure 16 - Model of Overflow ICUs and Floors

Modeling ICU and Floor Processes and Queues Based on Timestamps

This section discusses the technical model implementation of ICU and floor processes, as well as the calculation of the associated patient wait times.

Neuroscience Units

The neuroscience units are capacity constrained in the patient flow model. No more than 22 patients can be in the Lunder 6 ICU, and no more than 64 patients can be on the Lunder 7 and 8 Floors (combined) at any given time. The arrival times of patients who are being transferred to these units consequently depend on the availability of beds and the bed assignment decisions made by Admitting. The algorithm used for modeling this process is described in Appendix A.

Patients are initially considered to be in recovery during their stay in a unit. The recovery processes in Figure 15 and Figure 16 encompass all care processes that occur in the inpatient units before patients are medically ready to depart the units. The estimation of when patients are medically ready for transfer is described in Appendix D, Table 16. When patients are ready for transfer, they enter the post-recovery queue in Figure 15 or Figure 16 and wait to be transferred to their next location. Patients who are discharged do not incur wait times in the model. They depart the units at their historical departure times.

Note that this modeling approach has important implications for patients' lengths of stay in different inpatient units. We are assuming that patients' departure times are unaffected by changes to patients' arrival times. For example, if a patient arrives one hour earlier in the Lunder 6 ICU in a particular intervention scenario compared to the current state, this does not cause an equivalent shift in the patient's departure time from the ICU. In other words, earlier arrival times (as a result of decreases in ED and perioperative wait times) increase patients' lengths of stay in units. This assumption seems appropriate since most patients stay in inpatient units overnight. Changes to patients' intraday arrival times are therefore unlikely to affect patients' intraday departure times.

Overflow Units

The overflow units are not capacity constrained and patients arrive in these units at their historical arrival times. The patient arrival times are captured in the Patcom data and unaffected by the different intervention models.

Front-Door Clinical Admissions

In addition to MGH-internal transfers, the inpatient units also receive so-called front door clinical admissions. These are patients who are admitted to the hospital through channels other than the ED or the perioperative environment. Although, in reality, these patients generally visit some clinical location at the hospital (e.g., the catheterization laboratory, MRI scanner, etc.) before they arrive in one of the inpatient units, these patients are admitted directly to an inpatient unit in the model. This is necessitated by the fact that no historical data are available about patient flow in the aforementioned clinical locations. Front door clinical admissions are considered medically ready for transfer at their admission time, which is recorded in the historical data (see Table 3 and Appendix D, Table 16).

Calculation of Wait Times in Inpatient Units

Patient wait times in different inpatient units are currently not captured in the historical data. However, in order to model hospital-wide patient flow accurately, it is important to include in the model an appropriate proxy for transfer delays in inpatient units.

As explained previously in section 3.3, patients who are ready to transfer between different inpatient locations currently experience some of the longest delays. Patients who are ready to transfer from ICU beds to floor beds due to improvements in their medical conditions are strongly affected by this. These patients frequently spend additional days in the ICU before they are assigned and transferred to floor beds. In a number of cases these patients are even discharged directly from ICUs to their post-MGH destinations (e.g., 234 patients were discharged directly from the Lunder 6 ICU before July 1, 2013).

Given the dearth of available data, these multi-day delays are not captured in the model and patients are considered medically ready for transfer no more than 24 hours before their historical transfer time (see Appendix D, Table 16 for details). For this reason, wait times of these patients are not used directly to evaluate the effectiveness of different patient flow approaches. Instead, we capture the estimated wait times for these patients to ensure that wait time reductions in the ED and the perioperative environment do not occur at the expense of unit-to-unit transfers or front door clinical admissions.

Inpatient Transfers to Lunder 6, 7, and 8

The wait time calculation for patients who were transferred from another inpatient unit to one of the neuroscience units is illustrated in Figure 17. After patients are medically ready for transfer, they wait to receive a bed in their destination unit. The length of the bed wait depends on the availability of beds in the destination unit and the bed assignment decisions made by Admitting. The modeling of this process and the calculation of the resulting bed waits are explained in Appendix A.

After a bed becomes available in the patient's destination unit, the patient waits to be transferred from her current bed to her destination bed. The length of the transfer processing wait depends on the availability of transporters and other administrative factors. It is calculated from the historical data and held constant in all modeled scenarios.[26]

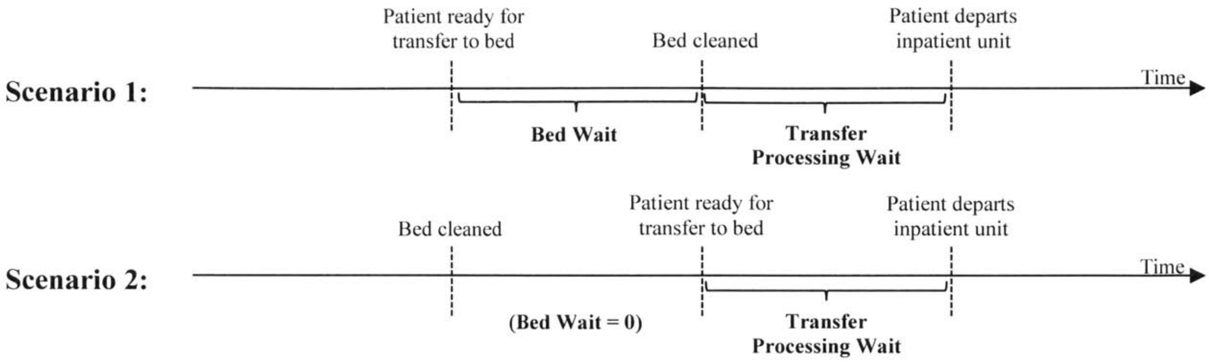


Figure 17 - Wait Time Illustration for Patients Transferring from Inpatient Units to Neuroscience Units and Clinical Front Door Admissions

Inpatient Transfers to Other Destinations at the Hospital

For patients who were transferred from an inpatient unit (either a neuroscience unit or an overflow unit) to an overflow unit or to the OR, the total wait (including the transfer processing wait) is the difference between the departure time (from the patient's current bed) and the patient ready time (see Appendix D, Table 16 for the calculation of the latter). Wait times of these patients are held constant in all simulated scenarios and not used to compare different bed management approaches.

4.3.4 Overall Model and Summary Statistics

Appendix B shows the combined patient flow model and Appendix C provides basic summary statistics for the cleaned data used in the simulation. Note that the summary statistics for the ED, the perioperative environment, and the overflow inpatient units are not representative of the actual patient flow in these parts of the hospital since the simulation only tracks inpatients who were either cared for by a

[26] The transfer processing wait is calculated as shown below. The patient departure time refers to the departure time from the bed that the patient occupied prior to her transfer to the neurosciences.

```
Transfer Processing Wait = Patient Departure Time - max(Patient Ready Time,
Bed Clean Time).
```

neuroscience team and/or who visited one of the neuroscience units during their stay. Inpatients that did not interact directly with the neurosciences and all outpatients are not considered explicitly in the model.

4.4 Performance Metrics

The patient flow model uses three primary performance metrics in order to evaluate the effectiveness of different operational interventions relative to the current state. First, it captures bed wait times for patients waiting for transfer to the neurosciences.[27] Bed wait times are analyzed separately for each possible origin-destination combination (e.g., ED-to-Lunder 7/8, ED-to-Lunder 6, Periop-to-Lunder 6, etc.). The bed wait time calculations of these patient populations are illustrated in Figure 9 (ED patients), Figure 14 (surgical patients), and Figure 17 (inter-unit transfer patients and clinical front door admissions).

The algorithm used to quantify bed wait times is outlined in Appendix A. The just-in-time bed assignment model requires a minor modification to this algorithm (discussed in Section 4.5.1).

In addition to individual bed wait times, the model tracks cumulative bed wait times that are unrelated to bed capacity constraints at the hospital. The cumulative delay unrelated to bed availability (DUBA) is defined as the total number of hours that patients wait for beds during the period of study while suitable beds are available in their destination units. Mathematically, the DUBA for unit i is defined as

$$\mathrm{DUBA}_i = \int_{t_0}^{t_{\max}} \min \begin{bmatrix} \text{Number of Patients Waiting for a Bed in Unit } i \\ \text{Number of Clean Beds in Unit } i \end{bmatrix} dt,$$

$$i = \text{Lunder 6 ICU, Lunder 7/8 Floors.}$$

Note that both the number of patients waiting for a bed and the number of clean beds are functions of time. The cumulative delay unrelated to bed availability is consequently the total patient wait time that can be

[27] This metric does not include the transfer processing wait times explained in the previous section. Transfer processing wait times are excluded since they are not associated with bed management practices (i.e. transfer processing wait times are incurred after the patient is ready and a clean bed is assigned to the patient).

eliminated through instantaneous just-in-time bed assignments for all patients. No additional bed capacity is required to eliminate this delay.

Just like the individual bed wait times, the cumulative delay unrelated to bed availability is calculated between January 1, 2012 (t_0) and June 30, 2013 ($t_{\max}$). The time between the opening of the Lunder building in early September 2011 and January 1, 2012 is modeled, but only considered as a "warm-up" period that allows the model to reach a steady state.

Finally, the model also tracks bed utilization in the neuroscience units. The utilization of each unit is the share of total capacity that is utilized by patients and bed cleanings during the period of study. Mathematically, the utilization is a defined as

$$\text{Bed Utilization}_i = 1 - \frac{\int_{t_0}^{t_{\max}} (\text{Number of Clean Beds in Unit } i)dt}{n_i(t_{max} - t_0\ )},$$

$$i = \text{Lunder 6 ICU, Lunder 7/8 Floors},$$

$$n_{\text{Lunder 6 ICU}} = 22, n_{\text{Lunder 7/8 Floors}} = 64.$$

In this formula, n_i is the total number of beds on unit i. The bed utilization is also calculated between January 1, 2012 (t_0) and June 30, 2013 ($t_{\max}$). The number of clean beds is once again a function of time.

4.5 Model Implementation of Interventions

The current state analysis suggests that (1) just-in-time bed assignments, (2) discharges earlier in the day, and (3) multi-day reductions in length of stay for patients with post-MGH inpatient care needs could yield significant wait time reductions and capacity for throughput increases. This section develops these three interventions in detail.

The discussion focuses on the development of realistic assumptions about the potential performance of the interventions. The section does not detail how this performance can be achieved. For example, Section

4.5.2 develops a daily discharge timetable that enables the neuroscience units to discharge patients earlier. It does not contain a detailed discussion of how current operations will have to change in order to achieve such a timetable. The goal is to analyze the effectiveness of different interventions and then have relevant hospital stakeholders determine the most cost-efficient and least disruptive ways to implement those operational changes that yield the most significant performance improvements in the simulation.

4.5.1 Just-in-time Bed Assignments

As discussed in Section 3.3, currently, bed-patient assignments are often made before either the patient is ready to be transferred to the bed or before the bed is cleaned and ready to receive the patient. This approach can cause patient wait hours that are unrelated to capacity constraints as explained in Figure 2. Using strict just-in-time bed assignments can significantly reduce these wait hours. Under such a policy, no patient is given a bed before she is clinically ready to be transferred to the bed (e.g., from the OR or the ED), and no bed is assigned to a patient before the bed is cleaned and ready to receive a patient. All patients who are clinically ready to be transferred to a particular inpatient unit are assigned to beds that become available in that unit on a strict first-ready, first-assigned basis.

By construction, instantaneous just-in-time bed assignments eliminate all DUBA. However, since bed assignments are not automated, some DUBA remains even under a strict just-in-time bed assignment policy. The remaining DUBA measures the aggregate time it takes bed managers to match up patients with beds after both are ready.

Implementation of Just-in-Time Bed Assignments

Just-in-time bed assignments require knowledge about patients' medical readiness for transfer. As discussed in previous sections, this information is currently only recorded directly for perioperative patients. For all other patient populations the medical readiness for transfer has to be estimated from other timestamps. The details of these calculations are discussed in Sections 4.3.1 and 4.3.3. Appendix D provides a summary for all patient transfers to neuroscience units.

As discussed previously, the estimation of patient ready times potentially reduces the accuracy of calculated patient wait times. This effect is most significant for patients who are transferred between different inpatient units. In particular, ICU-to-floor transfer patients are frequently medically ready to be moved from the ICU to a floor bed several days before the transfers actually happen.[28] These multi-day delays are caused by floor bed capacity constraints and the low bed placement priority of these patients relative to other patient populations (e.g., ED-to-floor and PACU-to-floor transfer patients). See Section 3.3 for more details. In the simulation, these patients are assumed to be medically ready less than 24 hours before their historical transfer time according to the formula outlined in Appendix D, Table 17. Multi-day transfer delays are not captured due to lack of available data.

These assumptions place a cap on the maximum wait time reduction that can be achieved for unit-to-unit transfer through just-in-time bed assignments (as well as through other interventions).[29] The accuracy of wait times for ED and surgical patients should only be minimally affected by this limitation.

Once patients are ready for transfer, they are assigned to beds that become available (i.e., are cleaned) at their intended destination (Lunder 6, or Lunder 7/8) on a first-come, first-served basis.[30] The bed assignment time is assumed to be normally distributed with a mean of 15 minutes and a standard deviation of five minutes. This time interval starts after the bed is cleaned and the patient is ready.

4.5.2 Discharges Earlier in the Day

The misalignment in the intraday timing of discharges and admissions suggests that earlier discharges could serve as an important way to free up bed capacity during peak times of the day. Since ED and OR inpatient bed needs are spread throughout the day, it does not seem necessary to discharge all patients in

[28] For a detailed analysis of this issue, see B.A. Christensen, "Improving ICU Patient Flow through Discrete-Event Simulation," master's thesis, Sloan School of Management and Engineering Systems Division, Massachusetts Institute of Technology, 2012.
[29] The time at which unit-to-unit transfer patients are medically ready for transfer is held constant across all scenarios (i.e., the current state simulation and the various intervention models).
[30] This is done by using the patient ready for transfer time from Appendix D, Table 17 instead of the CBEDs bed clean time in order to establish the transfer ranking discussed in Appendix A.

the morning. Instead, the focus should be on developing a discharge timetable that causes beds to become available in regular intervals throughout the day.

Table 6 shows the summary statistics for the daily number of discharges from the neuroscience ICU (Lunder 6) and floors (Lunder 7 and 8).

	Lunder 6	**Lunder 7/8 (combined)**
Days with discharges between the opening of the Lunder building in early September 2011 and July 1, 2013:	190	657
Distribution of discharges on those days:		
Minimum	1	1
25^{th} Percentile	1	9
Median	1	12
Mean	1.4	12.5
75^{th} Percentile	2	16
Maximum	8	27

Table 6 - Neuroscience Daily Discharge Statistics

On days with discharges, 13 patients are discharged from Lunder 7/8 and one patient is discharged from the Lunder 6 on average. Given these figures, we suggest a discharge timetable by which at least two of the day's floor discharges are completed each hour and one of the day's ICU discharges is completed each hour starting at a specified time in the morning. We will test different start times (i.e., 8 AM, 9 AM, 10 AM, and 11 AM) for this daily timetable in order to determine the sensitivity of patient wait times to discharge times. The total number of discharges per day is kept the same as in the original data.

Implementation of Discharges Earlier in the Day

The intervention model reassigns patients' discharge times so that at least two patients are discharged every hour beginning at a given start time (e.g., 8 AM). Patients who are discharged earlier in the historical data than what is required by the intervention keep their original discharge times.

Patients with discharges at night (i.e., 12 AM – 8 AM) and patients who expired are excluded from the intervention. These patients keep their historical departure time and they are not counted towards the daily discharge schedule. Table 7 illustrates the effect of the intervention on discharge times using a hypothetical example for a given day on Lunder 7 and 8.

		Intervention Discharge Times			
Historical Discharge Time	**Discharge Destination**	**8 AM Discharge Schedule**	**9 AM Discharge Schedule**	**10 AM Discharge Schedule**	**11 AM Discharge Schedule**
6:34 AM	Home	6:34 AM	6:34 AM	6:34 AM	6:34 AM
10:25 AM	Home	8 AM - 9 AM	9 AM - 10 AM	10:25 AM	10:25 AM
11:15 AM	Home	8 AM - 9 AM	9 AM - 10 AM	10 AM - 11 AM	11:15 AM
12:34 PM	SNF	9 AM - 10 AM	10 AM - 11 AM	11 AM - 12 PM	12 PM - 1 PM
2:37 PM	LTC Hospital	9 AM - 10 AM	10 AM - 11 AM	11 AM - 12 PM	12 PM - 1 PM
2:45 PM	Home	10 AM - 11 AM	11 AM - 12 PM	12 PM - 1 PM	1 PM - 2 PM
2:50 PM	Home	10 AM - 11 AM	11 AM - 12 PM	12 PM - 1 PM	1 PM - 2 PM
4:23 PM	Expired	4:23 PM	4:23 PM	4:23 PM	4:23 PM
5:25 PM	Home	11 AM - 12 PM	12 PM - 1 PM	1 PM - 2 PM	2 PM - 3 PM
7:11 PM	Home	11 AM - 12 PM	12 PM - 1 PM	1 PM - 2 PM	2 PM - 3 PM

Notes: The specific discharge times of patients who are discharged earlier in the interventions than in the historical data are sampled randomly from the one-hour time window indicated in the table.

Table 7 - Illustration of Earlier Discharge Times in Intervention Model

In this example the 10:25 AM discharge is not affected by the last two sensitivities of the intervention since the historical discharge time precedes the required discharge time. The same applies to the 11:15 AM discharge in the last sensitivity. These discharges are counted towards the schedule, meaning that only one additional patient is discharged between 10 AM and 11 AM in the 10 AM start time sensitivity (i.e., the 11:15 AM historical discharge), and no additional patients are discharged between 11 AM and 12 PM in the 11 AM start time sensitivity. Meanwhile, the 6:34 AM discharge and the 4:23 PM patient expiration are left unaffected by the intervention models, and these patient departures are not counted towards the discharge schedules.

Discharge Times for Patients Discharged from Lunder 7/8 Floors

Statistic	Historical Data	11 AM Discharge Schedule	10 AM Discharge Schedule	9 AM Discharge Schedule	8 AM Discharge Schedule
Minimum	12:09 AM	12:09 AM	12:09 AM	12:09 AM	12:09 AM
1st Percentile	9:30 AM	9:30 AM	9:30 AM	9:01 AM	8:02 AM
5th Percentile	10:52 AM	10:52 AM	10:14 AM	9:16 AM	8:17 AM
25th Percentile	1:08 PM	12:24 PM	11:33 AM	10:35 AM	9:37 AM
Median	2:48 PM	1:57 PM	1:11 PM	12:16 PM	11:15 AM
75th Percentile	4:47 PM	3:49 PM	3:07 PM	2:17 PM	1:19 PM
95th Percentile	7:15 PM	6:14 PM	5:40 PM	5:00 PM	4:14 PM
99th Percentile	8:53 PM	7:37 PM	7:10 PM	6:40 PM	5:50 PM
Max	11:55 PM	10:51 PM	9:23 PM	8:48 PM	7:58 PM
Mean	2:55 PM	2:09 PM	1:28 PM	12:34 PM	11:36 AM
N	6,938	6,938	6,938	6,938	6,938

Sources: Patcom

Notes: Analysis based on all 6,938 discharges from neuroscience floors (Lunder 7 and 8) between January 1, 2012 and June 30, 2013. Hospital-internal transfers (i.e., transfers from a neuroscience floor to another MGH location) and patient expirations are excluded.

Table 8 - Discharge Times for Patients Discharged from Lunder 7/8 in Scenarios with Discharges Earlier in the Day

The amount of time required for bed cleanings is assumed to be unaffected by the timing of discharges. For example, if a patient is discharged 53 minutes earlier in the intervention than in the historical data, her bed will also be cleaned 53 minutes earlier in the intervention than in the historical data.

Table 8 and Table 9 show the intraday distributions of discharges times for neuroscience discharges from the floors and the ICU, respectively, in the current state and intervention scenarios. Currently, half of all discharges from floors and the ICU occur after 2:48 PM and 2:19 PM, respectively. Five percent of patients are discharged after 7:15 PM and 6:32 PM, respectively.

Discharge Times for Patients Discharged from Lunder 6 ICU

Statistic	Historical Data	11 AM Discharge Schedule	10 AM Discharge Schedule	9 AM Discharge Schedule	8 AM Discharge Schedule
Minimum	8:16 AM	8:16 AM	8:16 AM	8:16 AM	8:00 AM
1st Percentile	9:35 AM	9:35 AM	9:35 AM	9:00 AM	8:03 AM
5th Percentile	10:32 AM	10:32 AM	10:02 AM	9:03 AM	8:06 AM
25th Percentile	12:21 PM	11:15 AM	10:17 AM	9:23 AM	8:26 AM
Median	2:19 PM	11:39 AM	10:40 AM	9:42 AM	8:46 AM
75th Percentile	3:53 PM	12:11 PM	11:14 AM	10:25 AM	9:18 AM
95th Percentile	6:32 PM	1:41 PM	12:43 PM	11:53 AM	10:59 AM
99th Percentile	8:08 PM	3:52 PM	3:30 PM	2:24 PM	1:49 PM
Max	10:25 PM	6:53 PM	5:30 PM	4:13 PM	3:48 PM
Mean	2:14 PM	11:51 AM	10:57 AM	10:02 AM	9:03 AM
N	234	234	234	234	234

Sources: Patcom

Notes: Analysis based on all 234 discharges from the neuroscience ICU (Lunder 6) between January 1, 2012 and June 30, 2013. Hospital-internal transfers (i.e., transfers from the neuroscience ICU to another MGH location) and patient expirations are excluded.

Table 9 - Discharge Times for Patients Discharged from Lunder 6 in Scenarios with Discharges Earlier in the Day

4.5.3 Multi-Day Length of Stay Reductions

Between January 1, 2012 and June 30, 2013, MGH discharged 1,610 patients from Lunder 7 and 8 to other inpatient facilities. The length of stay distributions for these patients are summarized in Figure 6 and Figure 7. Given the significantly longer lengths of stay for these patient populations compared to patients who are discharged to home or home health services, we conjecture that earlier patient transfers to post-MGH destinations could free up a significant amount of bed capacity at MGH and meaningfully reduce wait times for newly admitted patients.

As discussed previously in Section 3.4.3, patients discharged to other inpatient care facilities also experience longer lengths of stay because they are more ill, on average, than patients discharged to home. The available data does not enable us to distinguish between medical and administrative discharge delays. However, by applying the length of stay reductions only to those patients with the longest post-surgery, post-ICU lengths of stay in the current state, we are reducing the chance that patients with medical discharge delays are affected by the intervention.

As a general idea, these wait time reductions could be achieved through bed reservations at care facilities that MGH frequently discharges patients to.[31] Under such an arrangement, MGH could pay the facilities in question for a specified number of bed reservations per day or per week. If MGH failed to provide patients to fill the reserved beds by a specified point in time each day or week, the contracted facility would be able to accept patients from other facilities in order to fill these beds. Either way, the contract partner would retain the reservation charge paid by MGH.

These bed reservations can be thought of as real options. While the price of the options would create an additional expense for the hospital, this expense would likely be more than offset by the value of the ICU and floor bed capacity that is freed up at MGH itself.

Implementation of Multi-Day Length of Stay Reductions

The effect of these bed reservations is modeled as a decrease in MGH length of stay for patients who were transferred to other care facility after their discharge from the hospital. Specifically, the lengths of stay for all patients who were transferred to long-term care hospitals, rehabilitation hospitals, and skilled nursing facilities, and who were in the highest 25th percentile of their category in Figure 7, are reduced separately by one, two, three, and four days. This consequently affects all patients with a post-surgery, post-ICU length of stay of more than 13 days (long-term care hospitals), 7 days (rehabilitation hospitals), and 8 days (skilled nursing facilities), respectively. Between January 1, 2012 and June 30, 2013, a total of 452 patients are affected by this intervention, implying that approximately 450 (1 day earlier) to 1,800 bed-days (4 days earlier) of additional bed capacity could be created on the neuroscience floors.[32]

---

[31] The feasibility of this idea has not yet been tested.

[32] If the adjusted discharge day falls on a weekend or MGH holiday, the discharge day is set to the next business day that is not a holiday. This slightly reduces the additional bed capacity that is created.

The lengths of stay for all patients below these thresholds are left unchanged. This is a conservative assumption to minimize the chance that the intervention model affects patients whose lengths of stay were driven by their medical needs as opposed to capacity constraints at post-MGH care facilities. In reality, therefore, bed reservations would likely free up even more bed capacity than in our simulation. The intraday discharge and bed cleaning times are unaffected by this intervention model (i.e., the discharge times of affected patients change by an exact multiple of 24 hours).

5 Results

This section discusses the model results for both the current state model and the different operational interventions. Section 5.1 explains the model validation that was performed to ensure that the baseline results accurately reflect the current realities at the hospital. Sections 5.2 through 5.5 compare the results of the interventions introduced in Section 4.5 to the current state results. These sections focus primarily on wait times experienced by patients waiting in the ED and in the perioperative environment for transfer to the neuroscience inpatient units. While the wait times for other patient populations competing for space in the neurosciences (i.e., clinical front door admissions and unit-to-unit transfers) are also discussed, these wait times are not considered to be a primary performance metric for the different models due to the lack of accurate data about these patient populations (see Section 4.3.3 for more details). However, we track estimated wait times for these patients to ensure that performance improvements in the ED and the perioperative environment do not occur at the expense of other patient populations.

5.1 Model Validation

The wait times tracked by the patient flow simulation can also be calculated directly using the historical data. These historical wait time calculations are most accurate for patients waiting in the ED and in the perioperative environment since the data systems in these departments provide relatively detailed information about the bed cleaning and assignment process, as well as patients' readiness for transfer.

Historical wait times for other patient populations (e.g., unit-to-unit) can also be estimated, however, these calculations are expected to be less accurate since they are based on less detailed data.

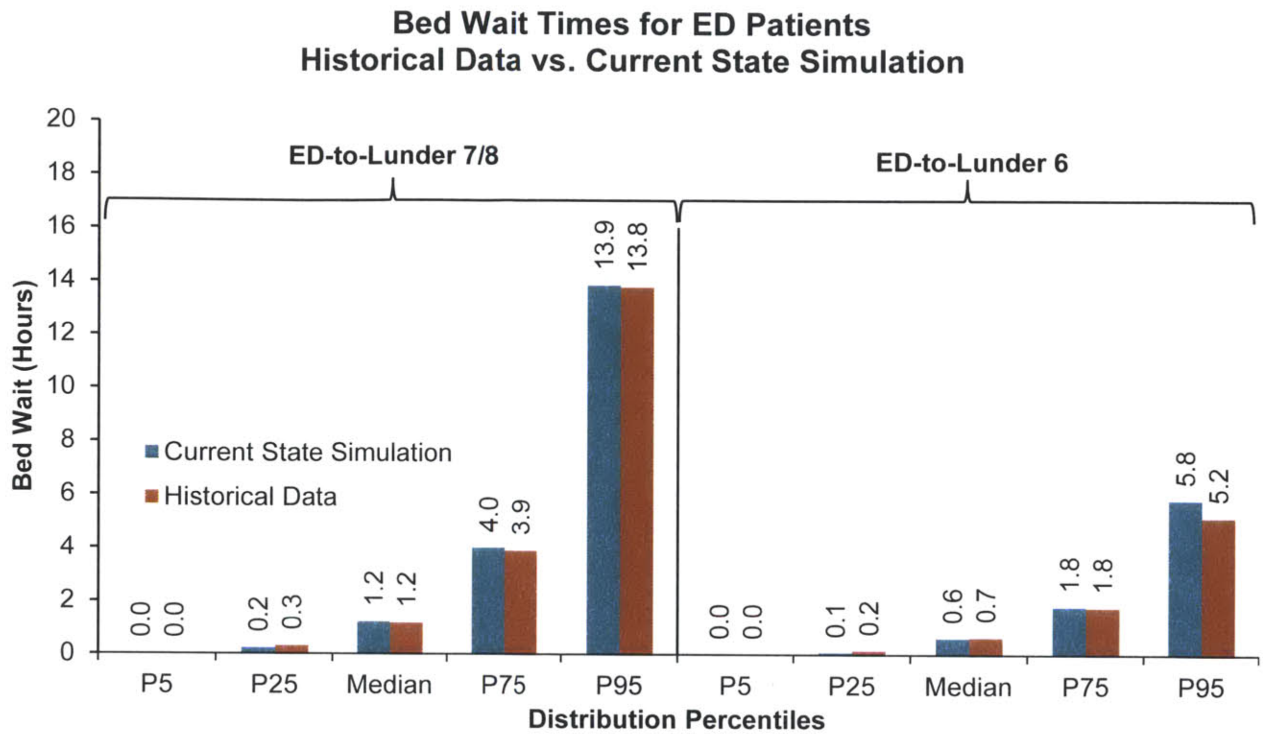
We use the historical wait times to verify the accuracy of our model assumptions and the correct functioning of the simulation. While we expect the baseline simulation to correspond closely to the current state at the hospital, we do not expect the distributions generated by the simulation model and the historical data to match exactly. Due to data limitations, as well as natural variability, small differences between the model and the historical data remain. However, we show that these differences have a negligible effect on wait time metrics. Furthermore, the differences do not affect the comparison of the baseline simulation and the different intervention models.

The most important sources of variation are the lack of historical data about bed closings, the inaccuracy of the CBEDs bed cleaning data, the exclusion of intra-unit patient transfers from the model, and the use of sampled bed assignment durations in the simulation.[33] These issues and their expected effects on the simulation are detailed in Appendix E.

5.1.1 Validation Results

Figure 18 compares historical bed wait times for patients waiting in the ED to the wait times calculated by the baseline simulation. The simulated mean wait times are within five minutes of their true historical values for both patients waiting for transfer to Lunder 7/8 (194 minutes vs. 195 minutes), and for patients waiting for transfer to Lunder 6 (83 minutes vs. 87 minutes). Similarly, the simulated median wait times for these units are within two minutes of their historical values. We find that predictions at the extreme ends of the wait time distributions are somewhat less accurate. However, even at the 95th percentile, the simulated wait times exceed the historical wait times by only four minutes for Lunder 7/8 and by 39 minutes for Lunder 6.

[33] Individual beds at MGH are occasionally closed (i.e., declared unavailable) for an extended time. Bed closings can occur for a variety of reasons, including staffing shortages, repairs, and maintenance.



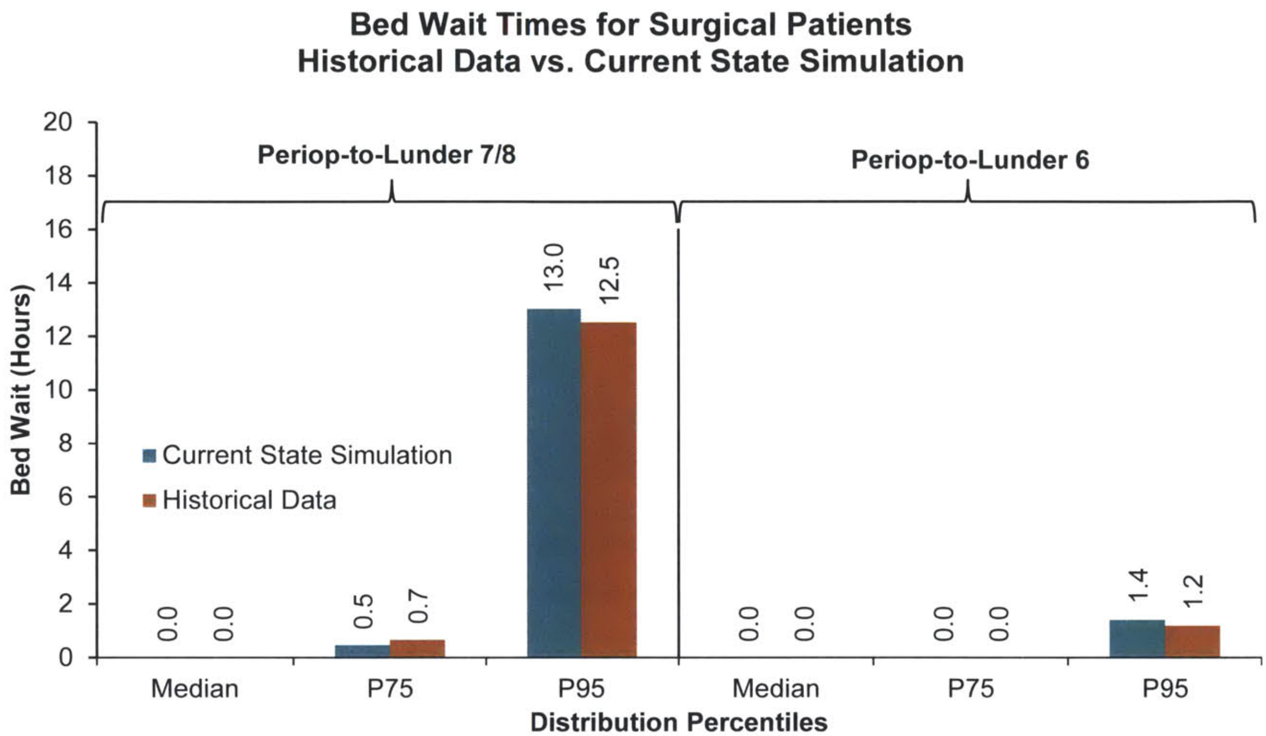
Sources: Patcom, Perioperative Case Data, EDIS, CBEDs, Simulation Results

Notes: Analysis based on ED transfers to neuroscience units between January 1, 2012 and June 30, 2013. Transfers that were in transit for more than 60 minutes after departure from the ED are excluded from comparison. These patients likely went to an unknown intermediate location before they were transferred to Lunder 6, 7, or 8. Hence, bed capacity constraints in the neurosciences might not have been the driving factor of their historical ED wait times. N = 2,247 (ED-to-Lunder 7/8); N = 889 (ED-to-Lunder 6).

Figure 18 - Bed Wait Times for ED Patients: Historical Data vs. Current State Simulation

These results indicate that there is no large or systematic offset between the historical values and the simulation results for Lunder 7/8. For Lunder 6, the simulated wait time distribution is slightly wider than the historical distribution. The differences between the distributions are likely caused by the simplifying model assumptions discussed in Appendix E.

Figure 19 shows the bed wait time statistics for patients waiting in the ORs and PACUs for transfer to the neuroscience units. Mean wait times for both ICU and floor patients are within two minutes of their historical values and there is no systematic offset between the simulation and the historical data. The majority of perioperative patients do not experience bed waits in the current state (both in the historical data and in the simulation). This result confirms our earlier findings (Section 3.3) regarding the current bed assignment process, which frequently matches surgical patients to beds in the morning before patients' surgeries are completed and patients are medically ready for transfer to an inpatient unit.



Sources: Patcom, Perioperative Case Data, CBEDs, Simulation Results

Notes: Analysis based on Periop-to-unit transfers between January 1, 2012 and June 30, 2013. Transfers that were in transit for more than 60 minutes after departure from Periop are excluded from comparison. These patients likely went to an unknown intermediate location before they were transferred to Lunder 6, 7, or 8. Hence, bed capacity constraints in the neurosciences might not have been the driving factor of their historical wait times. N = 1,978 (Periop-to-Lunder 7/8); N = 1,655 (Periop-to-Lunder 6).

Figure 19 - Bed Wait Times for Surgical Patients: Historical Data vs Current State Simulation

Appendix F provides a comprehensive comparison of historical bed wait times and simulated current state bed wait times for all patient populations. As expected, the simulated current state wait times for unit-to-unit transfers and clinical front door admissions are slightly less accurate than for ED and perioperative patients. However, the wait times for these two patient groups are still reasonably close to their historical values given the quality and granularity of the Patcom and CBEDs data. No systematic offset between the historical data and the simulated results can be observed.

Finally, we also compare the historical and simulated wait time distributions for ED and perioperative patients pairwise using the Wilcoxon rank sum test. The detailed results are shown in Table 10.

	Wait Time (Minutes)							
Quantile	ED-to-Lunder 7/8 Transfers		ED-to-Lunder 6 Transfers		Periop-to-Lunder 7/8 Transfers		Periop-to-Lunder 6 Transfers	
100.0%	2,040	2,040	1,245	1,620	2,245	2,245	1,115	1,115
99.5%	1,234	1,267	728	978	1,501	1,501	354	422
97.5%	1,029	1,018	412	471	1,182	1,181	145	180
90.0%	644	647	219	222	250	239	23	23
75.0%	234	240	108	109	40	28	0	0
50.0%	70	72	39	37	0	0	0	0
25.0%	18	13	9	4	0	0	0	0
10.0%	0	0	0	0	0	0	0	0
2.5%	0	0	0	0	0	0	0	0
0.5%	0	0	0	0	0	0	0	0
0.0%	0	0	0	0	0	0	0	0
Summary Statistics								
Mean	194.2	195.0	82.7	87.2	97.7	97.4	11.9	14.2
St. Dev.	281.5	282.4	118.3	145.8	272.6	275.1	52.9	63.9
St. Err. Mean	5.9	6.0	4.0	4.9	6.1	6.2	1.3	1.6
Upper 95% Mean	205.8	206.7	90.5	96.8	109.7	109.6	14.4	17.3
Lower 95% Mean	182.5	183.3	74.9	77.6	85.7	85.3	9.3	11.1
N	2,247	2,247	889	889	1,978	1,978	1,655	1,655
Wilcoxon Rank Sum Test (H_0: $\delta = 0$; H_a: $\delta \neq 0$)								
W (*p*-value)	2,584,626 (0.1662)		411,270 (0.1355)		1,994,586 (0.1891)		1,371,943 (0.8801)	

Table 10 - Statistical Comparison of Wait Time Distributions

For the reader's convenience, we include the following, slightly modified, description of the Wilcoxon rank sum test from J.H. McDonald, *Handbook of Biological Statistics*, Sparky House Publishing, 2nd ed., 2009.

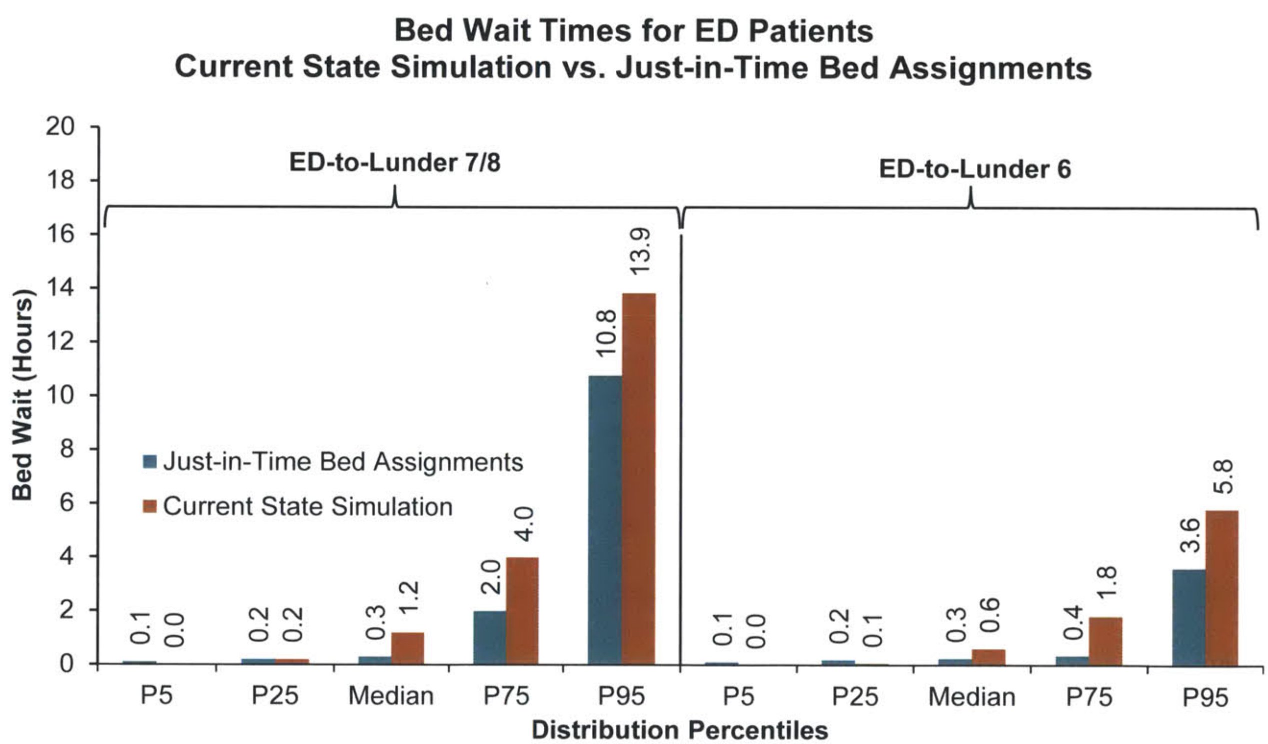
> The Wilcoxon rank sum test (also known as the Mann–Whitney U-test, Mann–Whitney–Wilcoxon test, or the Wilcoxon two-sample test) is the non-parametric analogue of the Student's t-test. The Wilcoxon rank sum test does not assume that the data are normally distributed; that is its big advantage. It does, however, assume that the observations in each group come from populations with the same shape of distribution. The null hypothesis is that the samples come from populations such that the probability that a random observation from one group is greater than a random observation from another group is 0.5.

Since visual inspection of the sample histograms reveals that they are highly non-normal, the Wilcoxon rank sum test is appropriate. The Wilcoxon rank sum test fails to reject the null hypothesis that the wait times were drawn from identical distributions (p-values between 0.13 and 0.88).

Given these results, we conclude that the baseline simulation accurately reflects the current neuroscience patient flow at the hospital. The model assumptions and data issues discussed in Appendix E do not have a significant effect on the accuracy of the model.

5.2 Results of Just-in-Time Bed Assignments

Figure 20 compares current bed wait times for ED patients to wait times that could be achieved using just-in-time bed assignments.



Sources: Patcom, Perioperative Case Data, EDIS, CBEDs, Simulation Results

Notes: Analysis based on ED transfers to neuroscience units between January 1, 2012 and June 30, 2013. Transfers that were in transit for more than 60 minutes after departure from the ED are excluded from comparison. These patients likely went to an unknown intermediate location before they were transferred to Lunder 6, 7, or 8. Hence, bed capacity constraints in the neurosciences might not have been the driving factor of their historical ED wait times. N = 2,247 (ED-to-Lunder 7/8); N = 889 (ED-to-Lunder 6).

Figure 20 - Bed Wait Times for ED Patients: Current State Simulation vs. Just-in-Time Bed Assignments

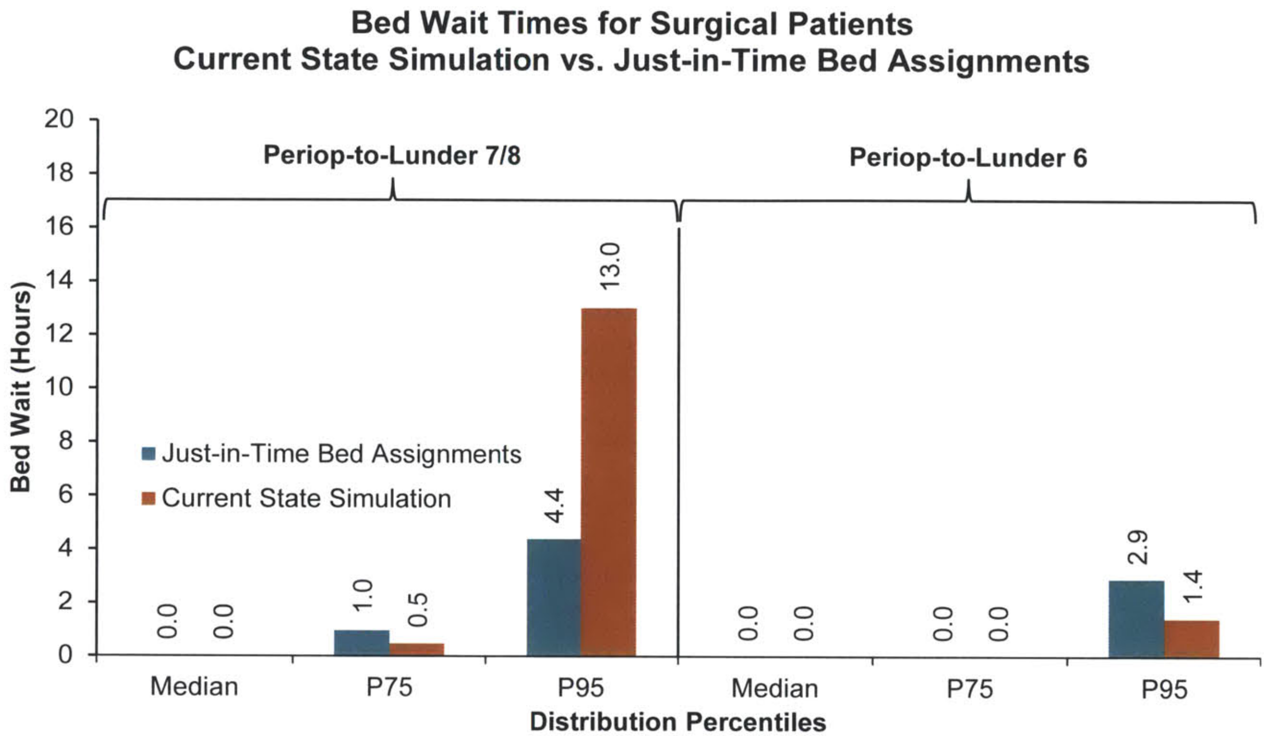
Just-in-time bed assignments reduce average ED wait times for floor and ICU patients by 68 minutes (35%) and 42 minutes (48%), respectively. Median wait times decrease by 54 minutes (75%) and 22 minutes (59%), respectively.

Just-in-time bed assignments have the most dramatic impact on patients with exceptionally high wait times in the current state. Bed wait times for patients in the 95th percentile decrease by more than three hours and two hours, respectively. Meanwhile, patients with zero or very short wait times in the current state see their wait times increase (i.e., the 5th percentile increases from zero minutes to seven minutes for both floor and ICU patients). Hence, just-in-time bed assignments not only decrease average wait times significantly, but also cause a more equitable distribution of wait times among patients.

Figure 21 shows the same comparison for patients waiting in the perioperative environment for transfer to Lunder 7/8 and Lunder 6. For floor patients, we observe the same general changes as in the ED. The average bed wait time decreases by 35 minutes (36%). Patients with long wait times benefit significantly more (the 95th percentile decreases by more than 8.6 hours or 66%), while patients with short wait times see a slight increase in their wait times (e.g., by 30 minutes at the 75th percentile).

As shown in Appendix F, just-in-time bed assignments increase the average wait time for surgical patients requiring ICU-level care by ten minutes. The percentage of these patients with non-zero bed wait times increases from 15% (214 patients) to 22% (297 patients).

This result is expected since this patient population is currently heavily prioritized over other patient populations in order to avoid bottlenecks in the OR. Since surgical patients who require ICU-level care are generally brought directly from the OR to a bed in the Lunder 6 ICU, bed wait times for these patients can cause costly delays in follow-on cases in the OR. For this reason Admitting prioritizes these patients and tries to reserve beds for them before their surgeries are completed.



Sources: Patcom, Perioperative Case Data, CBEDs, Simulation Results

Notes: Analysis based on Periop-to-unit transfers between January 1, 2012 and June 30, 2013. Transfers that were in transit for more than 60 minutes after departure from Periop are excluded from comparison. These patients likely went to an unknown intermediate location before they were transferred to Lunder 6, 7, or 8. Hence, bed capacity constraints in the neurosciences might not have been the driving factor of their historical wait times. N = 1,978 (Periop-to-Lunder 7/8); N = 1,655 (Periop-to-Lunder 6).

Figure 21 - Bed Wait Times for Surgical Patients: Current State Simulation vs. Just-in-Time Bed Assignments

In order to avoid bottlenecks in the OR, more of these patients will have to be brought to a PACU before their transfer to Lunder 6 under a just-in-time bed assignment policy. While this is not desirable, the additional volume is manageable. The 7% increase in patients with positive wait times implies that at most 83 additional ICU patients would have to be accommodated in the PACU over the 18-month period of study (i.e., one additional patient every 6.5 days).

Alternatively, the just-in-time policy can be modified to address this issue. Instead of assigning surgical ICU patients to beds when their surgeries are finished, these patients could be assigned slightly earlier. Specifically, we find that assigning these patients to beds starting approximately 45 minutes prior to the expected completion of surgery will reduce post-surgical delays back to current levels.

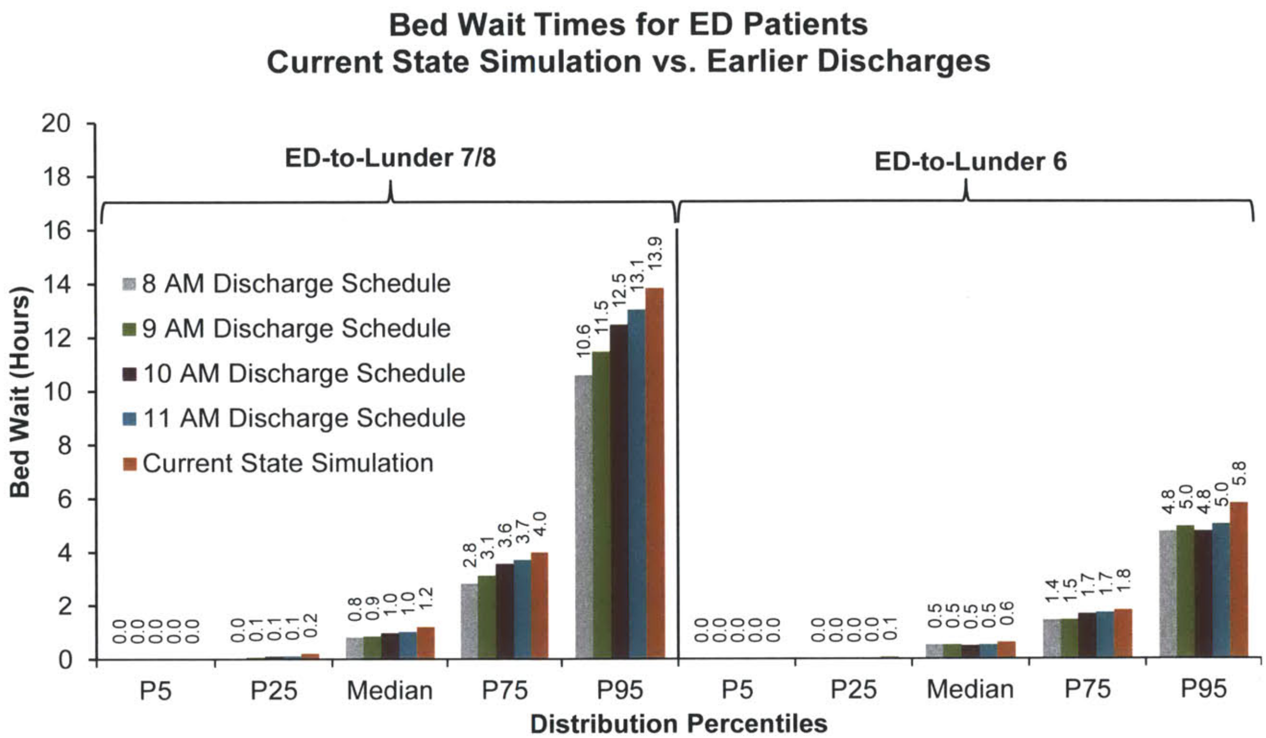
Delays for ICU patients are also the subject of ongoing work at the hospital. Specifically, the MIT – MGH collaboration is investigating approaches for reducing transfer delays for ICU patients who are medically ready for transfer to a floor bed. Addressing this problem will create additional ICU bed capacity and therefore also reduce post-surgical delays for critically ill patients.

Appendix F shows the change in bed wait times for front door clinical admissions and unit-to-unit transfers. We find that these patient populations experience shorter average delays as a result of just-in-time bed assignments. Gains in the ED and the perioperative environment consequently do not occur at the expense of other patient populations.

Finally, the cumulative delay that is unrelated to bed availability (DUBA) during the 18-month period of study decreases from 221 days to 14 days for Lunder 7/8 patients, and from 45 days to eight days for Lunder 6 patients through the implementation of just-in-time bed assignments. The remaining DUBA reflects the cumulative effect of bed assignment delays for ED patients. As discussed in Section 4.5.1, bed assignments for ED patients are assumed to take 15 minutes on average after a patient is ready for transfer and a clean bed is available.

5.3 Results of Discharges Earlier in the Day

Figure 22 shows ED bed wait time statistics for different scenarios with discharges earlier in the day. The wait time reductions achieved as a result of earlier discharges are significantly lower than those achieved through just-in-time bed assignments. Under the most aggressive assumptions (i.e., discharge schedules starting at 8 AM), average wait times for floor and ICU patients decrease by 50 minutes (26%) and 13 minutes (15%), respectively. Median wait times decrease by 23 minutes (32%) and six minutes (16%), respectively. Wait time reductions for less ambitious schedules are lower.



Sources: Patcom, Perioperative Case Data, EDIS, CBEDs, Simulation Results

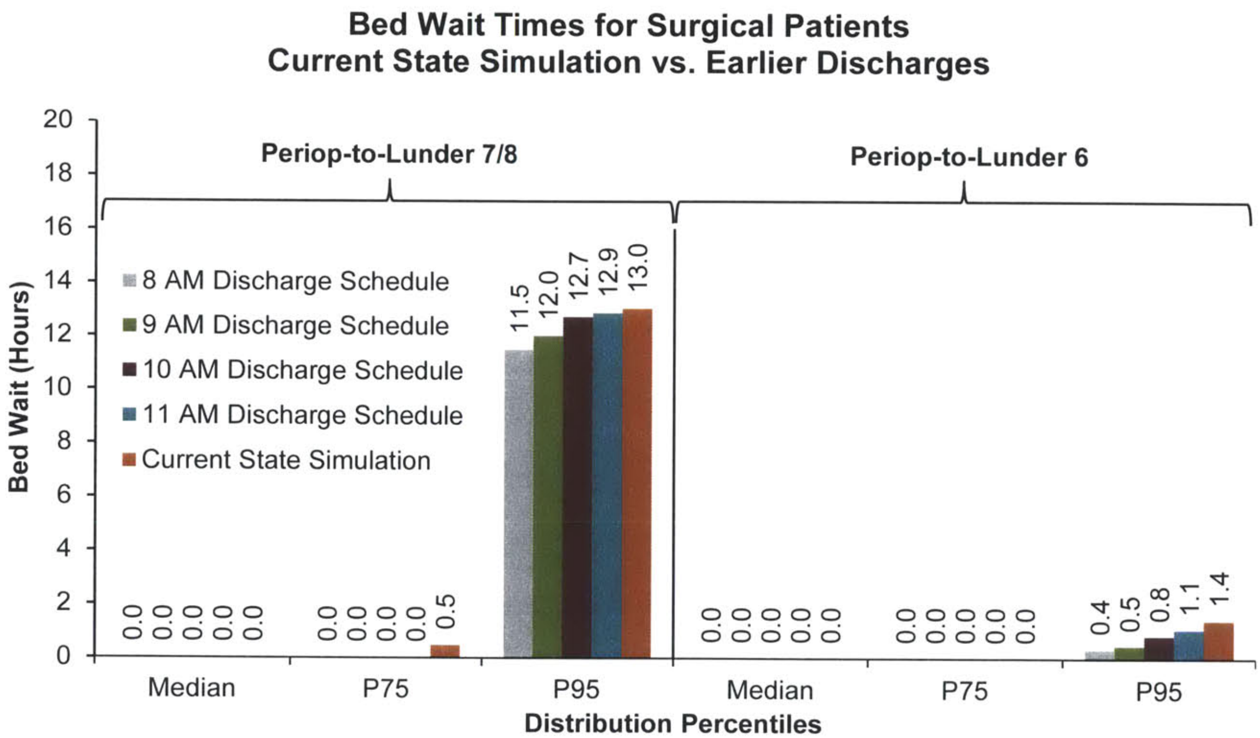
Notes: Analysis based on ED transfers to neuroscience units between January 1, 2012 and June 30, 2013. Transfers that were in transit for more than 60 minutes after departure from the ED are excluded from comparison. These patients likely went to an unknown intermediate location before they were transferred to Lunder 6, 7, or 8. Hence, bed capacity constraints in the neurosciences might not have been the driving factor of their historical ED wait times. N = 2,247 (ED-to-Lunder 7/8); N = 889 (ED-to-Lunder 6).

Figure 22 - Bed Wait Times for ED Patients: Current State Simulation vs. Earlier Discharges

As shown in Figure 22, bed wait times for patients transferring from the ED to Lunder 6 do not decrease consistently when discharge times are moved to earlier in the day. Specifically, the 95th percentile of the wait time distribution increases from 286 minutes (4 hours and 46 minutes) to 297 minutes (4 hours and 57 minutes) as we move from the 10 AM discharge schedule to the 9 AM discharge schedule.

This effect results from an increase in bed assignment durations. As explained in Section 4.3.1, the bed assignment durations are sampled from a distribution that depends on the bed cleaning duration. See Figure 10 and Figure 12 for details. As bed cleaning durations decrease, the average bed assignment duration increases. In this particular case, the increase in bed assignment durations is greater than the decrease in bed cleaning durations. Since the bed wait is the sum of the wait for bed cleaning and the wait for bed assignment, the bed wait also slightly increases.

A close examination of the data shows that many ED patients transferring to Lunder 6 experience bed cleaning durations between 1 minute and 5 hours in the 10 AM discharge schedule scenario. As we move to the 9 AM discharge schedule, a significant number of these patients now experience zero bed cleaning durations (and, therefore, zero wait times for bed cleaning). In other words, a clean bed on Lunder 6 is available for them at the time of their bed request. Looking at Figure 12, however, we find that the average bed assignment duration increases significantly as we move from non-zero bed cleaning durations to zero cleaning durations, causing the increase in bed wait times observed in Figure 22.



Sources: Patcom, Perioperative Case Data, CBEDs, Simulation Results

Notes: Analysis based on Periop-to-unit transfers between January 1, 2012 and June 30, 2013. Transfers that were in transit for more than 60 minutes after departure from Periop are excluded from comparison. These patients likely went to an unknown intermediate location before they were transferred to Lunder 6, 7, or 8. Hence, bed capacity constraints in the neurosciences might not have been the driving factor of their historical wait times. N = 1,978 (Periop-to-Lunder 7/8); N = 1,655 (Periop-to-Lunder 6).

Figure 23 - Bed Wait Times for Surgical Patients: Current State Simulation vs. Earlier Discharges

Earlier discharges also only provide limited benefits in the perioperative environment (Figure 23). The 8 AM discharge schedule is the only one that achieves an average wait time reduction in excess of 30 minutes (33%) for floor patients. We also note that discharges earlier in the day do not have a strong systematic effect on DUBA. See Appendix H for details.

The limited effectiveness of earlier discharges becomes even more evident when we compare the wait time reductions to the associated shifts in discharge times. The 8 AM discharge schedule scenario requires the average discharge time for patients on Lunder 7/8 to be more than 3.3 hours earlier than in the current state. However, patients who are waiting in the ED and the perioperative environment for a bed on Lunder 7/8 only experience average wait time reductions of 50 minutes (26%) and 32 minutes (33%), respectively. Earlier discharges without other interventions consequently do not generate dramatic performance improvements, especially considering the amount of effort required to change discharge processing in the affected units.

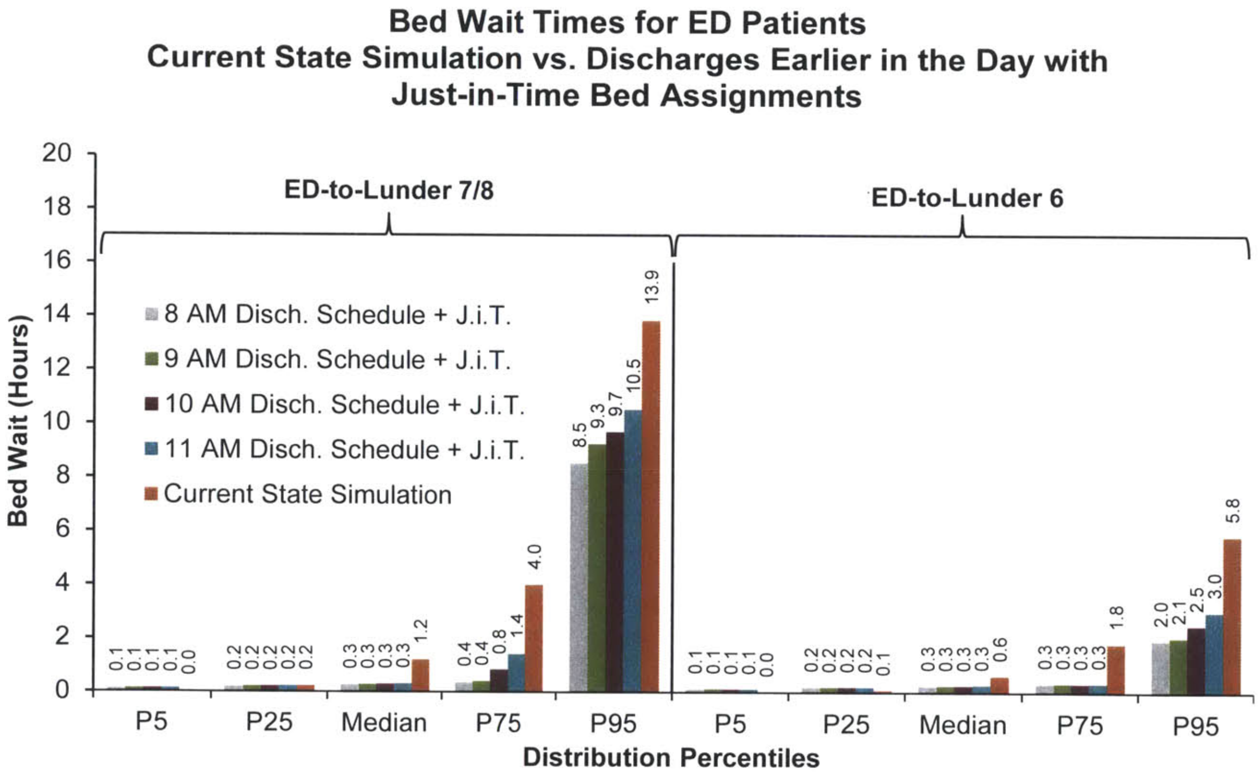
Two important factors contribute to the relatively limited impact of earlier discharges. First, the additional capacity generated through earlier discharges does not line up with the timing of bed needs for newly admitted patients. While discharges do occur earlier in the day, the discharge process is still not linked directly to the timing of admissions under our modeling assumptions, and discharge times are consequently not responsive to the timing of admissions on any given day. As a result, a significant share of the additional capacity generated through earlier discharges does not actually benefit waiting patients.

The bed utilizations illustrate this effect. Earlier discharges reduce bed utilization of the neuroscience floors by 0.6% to 2.7%, and bed utilization of the neuroscience ICU by 0.4% to 1.2%. See Appendix G for detailed results. Consequently, a significant share of the bed capacity created through earlier discharges is not utilized effectively at current throughput levels. Instead, beds are idle more frequently.

Second, the current bed assignment processes at the hospital diminish the effect of earlier discharges. As discussed in Section 4.3.1, bed assignment durations for ED patients are strongly correlated with bed cleaning durations. Earlier discharges reduce bed cleaning durations for ED patients, which can be thought of as a shift to the left along the x-axis in Figure 11 and Figure 12. This causes the average bed assignment durations to increase and performance improvements to be diminished.

5.4 Results of Discharges Earlier in the Day and Just-in-Time Bed Assignments

The effect of longer bed assignment durations discussed in the previous section can be eliminated by combining the different discharge schedules with just-in-time bed assignments. The resulting wait times for ED patients are shown in Figure 24.

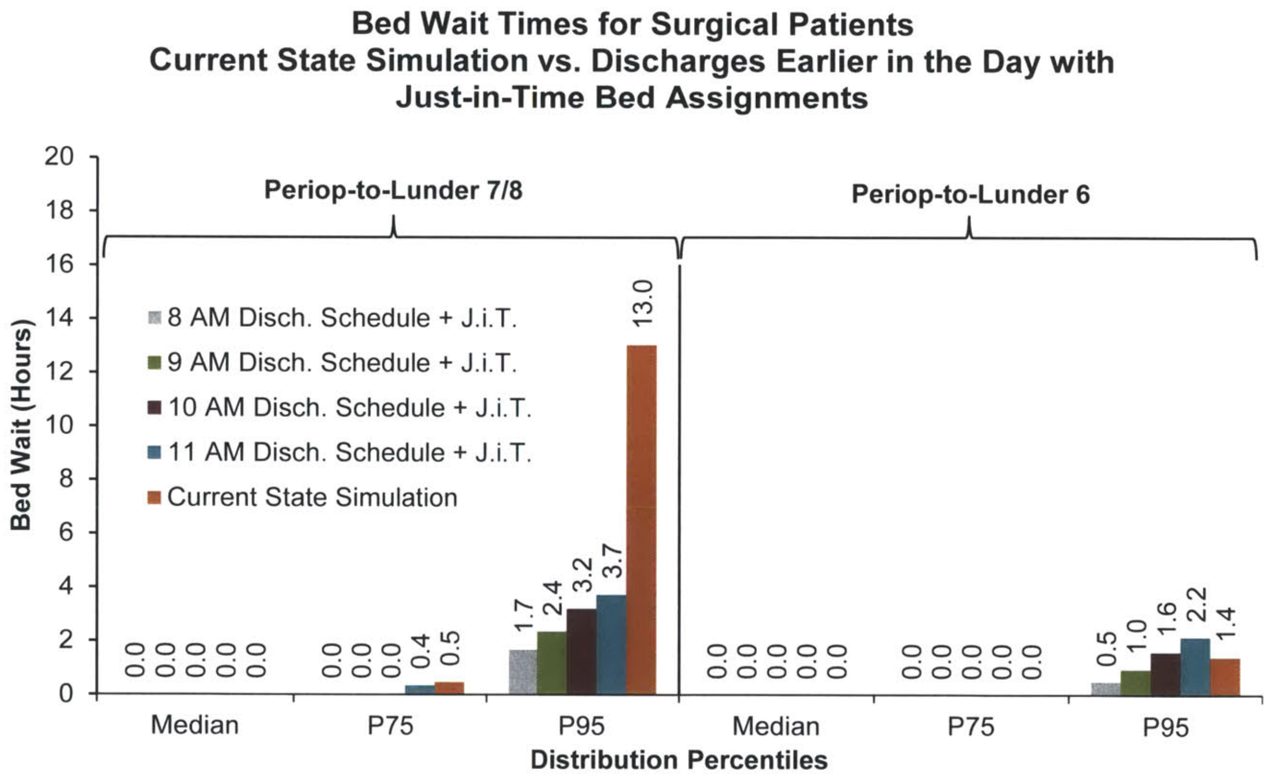


Sources: Patcom, Perioperative Case Data, EDIS, CBEDs, Simulation Results

Notes: Analysis based on ED transfers to neuroscience units between January 1, 2012 and June 30, 2013. Transfers that were in transit for more than 60 minutes after departure from the ED are excluded from comparison. These patients likely went to an unknown intermediate location before they were transferred to Lunder 6, 7, or 8. Hence, bed capacity constraints in the neurosciences might not have been the driving factor of their historical ED wait times. N = 2,247 (ED-to-Lunder 7/8); N = 889 (ED-to-Lunder 6).

Figure 24 - Bed Wait Times for ED Patients: Current State Simulation vs. Discharges Earlier in the Day with Just-in-Time Bed Assignments

The results show that the wait time reduction achieved by the combined interventions is approximately the sum of the wait time reductions achieved by just-in-time bed assignments and earlier discharges separately. Hence, these two interventions seem complementary to each other. For example, the 8 AM discharge schedule combined with just-in-time bed assignments reduces average ED bed wait times for floor patients by 111 minutes (57%), while the interventions individually reduce average wait times by 68 minutes (35%) and 50 minutes (26%), respectively. Figure 25 shows that the same holds for patients waiting in the PACUs for transfer to Lunder 7/8.



Sources: Patcom, Perioperative Case Data, CBEDs, Simulation Results

Notes: Analysis based on Periop-to-unit transfers between January 1, 2012 and June 30, 2013. Transfers that were in transit for more than 60 minutes after departure from Periop are excluded from comparison. These patients likely went to an unknown intermediate location before they were transferred to Lunder 6, 7, or 8. Hence, bed capacity constraints in the neurosciences might not have been the driving factor of their historical wait times. N = 1,978 (Periop-to-Lunder 7/8); N = 1,655 (Periop-to-Lunder 6).

Figure 25 - Bed Wait Times for Surgical Patients: Current State Simulation vs. Discharges Earlier in the Day with Just-in-Time Bed Assignments

In addition, Figure 25 shows that wait times for patients transferring from the perioperative environment to Lunder 6 increase slightly at the 95th percentile as we move from the current state simulation to the

11 AM discharge schedule scenario with just-in-time bed assignments. This increase results from the implementation of just-in-time bed assignments. Just-in-time bed assignments cause this patient population to be prioritized slightly less than in the current state. The same effect was observed in the case of just-in-time bed assignments without earlier discharges. See Section 5.2, Figure 21. However, combining just-in-time bed assignments with more aggressive discharge schedules (i.e., 10 AM, 9 AM, or 8 AM) causes bed wait times at the 95^{th} percentile to decrease relative to the current state.

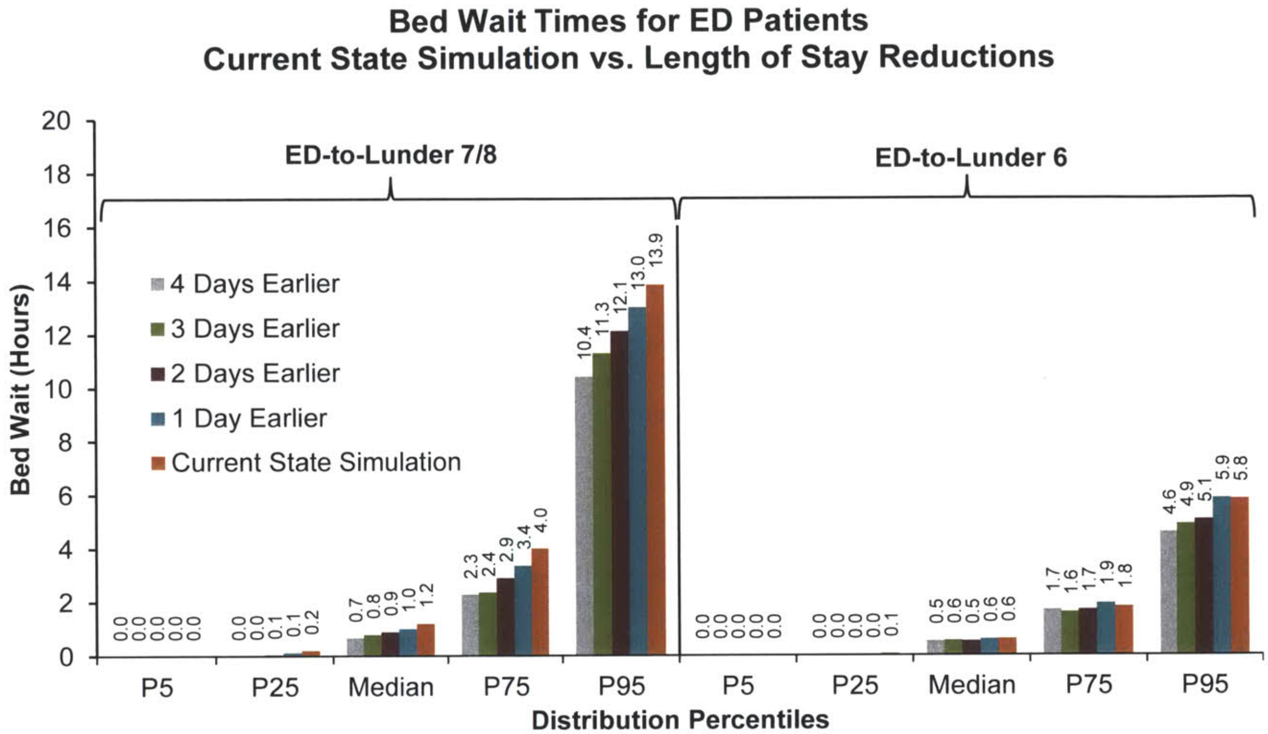
The decline in DUBA resulting from the combined interventions is approximately equal to the decline achieved through just-in-time bed assignments alone. This is expected since earlier discharges do not have a strong systematic effect on DUBA. The combined interventions cause DUBA to drop from 45 days to 9 days for Lunder 6, and from 221 days to 18 days for Lunder 7/8. See Appendix H for details.

Furthermore, the combination of earlier discharges and just-in-time bed assignments causes bed utilization in the neuroscience units to decrease about as much as through the implementation of earlier discharges alone. This is expected since just-in-time bed assignments do not have a strong effect on bed utilization (see Appendix G for details).

5.5 Results of Multi-Day Length of Stay Reductions

Figure 26 shows the change in ED wait times as a result of length of stay reductions for patients who are being discharged to other inpatient care facilities. As discussed in Section 4.5.3, in these interventions the length of stay of a quarter of the patients discharged to long-term care hospitals, skilled nursing facilities, and rehabilitation hospitals is reduced separately by one, two, three, and four days. The intraday discharge time is kept the same as in the historical data and the throughput is held constant.

Average wait times for floor patients decrease between 23 minutes (discharge one day earlier) and 68 minutes (four days earlier). This corresponds to average wait time reductions of 12% and 35%, respectively. Median wait times decrease by eleven minutes (15%) and 32 minutes (44%), respectively. Meanwhile, average wait times for ED patients requiring ICU-level care decrease by at most 10 minutes or 12% (four days earlier). Median wait times decrease by up to five minutes (14%). Reducing the length of stay by one day does not result in any wait time reductions ED patients transferring to Lunder 6.



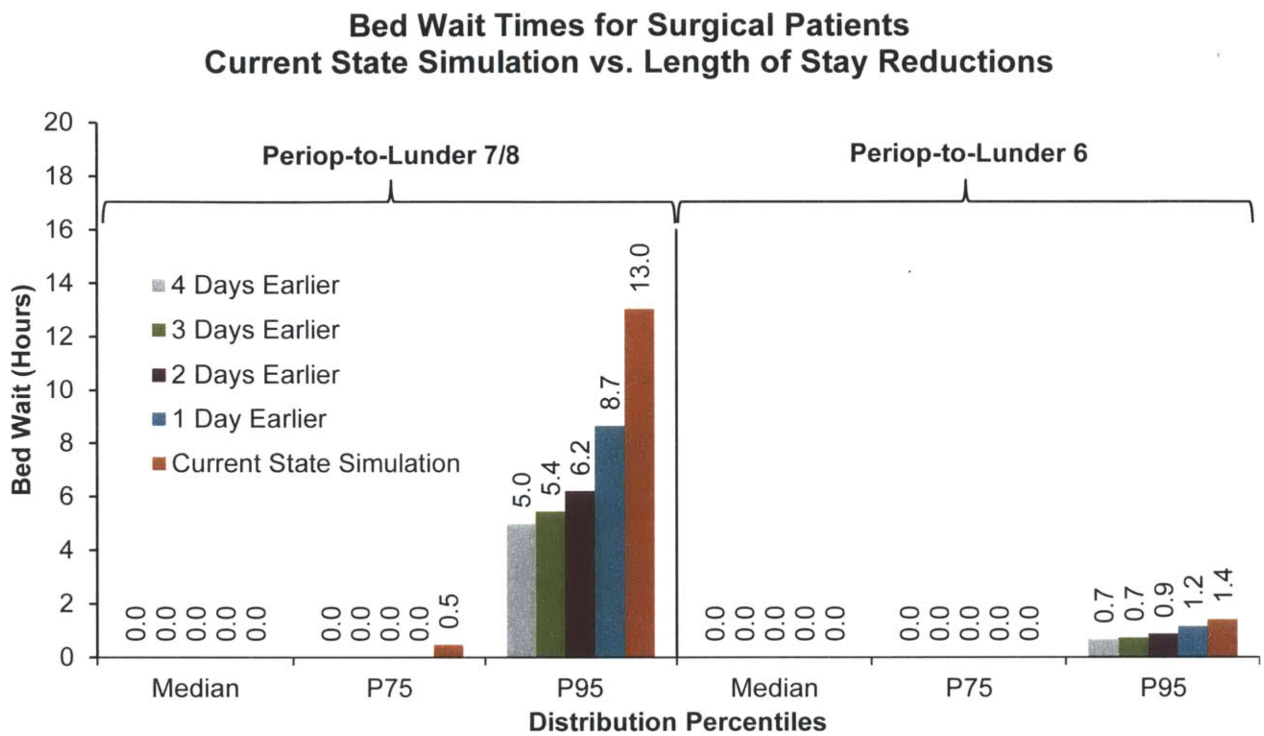
Sources: Patcom, Perioperative Case Data, EDIS, CBEDs, Simulation Results

Notes: Analysis based on ED transfers to neuroscience units between January 1, 2012 and June 30, 2013. Transfers that were in transit for more than 60 minutes after departure from the ED are excluded from comparison. These patients likely went to an unknown intermediate location before they were transferred to Lunder 6, 7, or 8. Hence, bed capacity constraints in the neurosciences might not have been the driving factor of their historical ED wait times. N = 2,247 (ED-to-Lunder 7/8); N = 889 (ED-to-Lunder 6).

Figure 26 - Bed Wait Times for ED Patients: Current State Simulation vs. Length of Stay Reductions

Figure 27 shows the wait time reductions for surgical patients. Floor patients with exceptionally long bed wait times (i.e., in the 95th percentile) benefit significantly from multi-day length of stay reductions. These patients see average wait times decrease between 4.4 hours (one day earlier) and 8.1 hours (four days earlier), corresponding to wait time reductions of 34% and 62%, respectively. Meanwhile, bed wait times for patients with short or zero wait times in the current state do not change significantly.

Surgical patients transferring to the Lunder 6 ICU do not experience significant wait times in the current state simulation. The average wait time of these patients decreases by up to five minutes (36%) as a result of earlier discharges.



Sources: Patcom, Perioperative Case Data, CBEDs, Simulation Results

Notes: Analysis based on Periop-to-unit transfers between January 1, 2012 and June 30, 2013. Transfers that were in transit for more than 60 minutes after departure from Periop are excluded from comparison. These patients likely went to an unknown intermediate location before they were transferred to Lunder 6, 7, or 8. Hence, bed capacity constraints in the neurosciences might not have been the driving factor of their historical wait times. N = 1,978 (Periop-to-Lunder 7/8); N = 1,655 (Periop-to-Lunder 6).

Figure 27 - Bed Wait Times for Surgical Patients: Current State Simulation vs. Length of Stay Reductions

Appendix F provides additional wait times for unit-to-unit transfers and clinical front door admissions. These two patient categories also see their wait times decrease as a result of length of stay reductions. The performance improvements in the ED and the perioperative environment consequently do not occur at the expense of other patients.

The decreases in intraday wait times due to multi-day length of stay reductions are significant on an absolute scale. However, the decreases are modest considering the large amount of additional floor bed capacity that is created, and the amount of effort that is likely required in order to implement this intervention. In addition, this intervention slightly increases DUBA at current throughput levels as seen in Appendix H.

As discussed in Section 4.5.3, length of stay reductions create approximately 450 (one day earlier) to 1,800 bed-days (four days earlier) of additional bed capacity on Lunder 7 and 8 during the 18-month period of study. In other words, 1.3% (one day earlier) to 5.1% (four days earlier) of the total bed capacity on these floors during this time period is freed up as a result of length of stay reductions. Appendix G shows that the majority of this additional capacity goes toward decreases in bed utilization instead of wait time reductions. Bed utilization of the floors decreases between 1.0% (one day earlier) and 4.2% (four days earlier). This result indicates that the timing of the additional capacity generally does not match the timing of patient waits in the ED and in the perioperative environment. Hence, reducing patients' lengths of stay is an effective way to create capacity for potential additional throughput, but not a very effective way to decrease patients' intraday waits at current throughput levels.

As shown in Appendix H, the DUBA does not decrease as a result of length of stay reductions since this intervention does not make changes to the bed assignment process.

5.6 Summary of Results

Table 11 provides a summary of wait times for ED patients transferring to the neuroscience units in the different scenarios. Table 12 summarizes the same information for surgical patients in the perioperative environment.

Wait Times of ED Patients Transferring to Neuroscience Units

	Wait Times (hh:mm)													
	Periop-to-Lunder 7/8 Transfers							Periop-to-Lunder 6 Transfers						
Scenario	P5	P25	Median	Mean	P75	P95	Max	P5	P25	Median	Mean	P75	P95	Max
Historical Data	0:00	0:18	1:10	3:14	3:54	13:47	34:00	0:00	0:09	0:39	1:23	1:47	5:10	20:45
Current State Simulation	0:00	0:13	1:12	3:15	4:00	13:51	34:00	0:00	0:04	0:37	1:27	1:49	5:49	27:00
Just-in-Time Bed Assign.	0:07	0:13	0:18	2:07	2:00	10:47	21:58	0:07	0:12	0:15	0:45	0:21	3:37	19:46
Earlier Discharges														
11 AM Discharge Schedule	0:00	0:07	1:01	3:01	3:43	13:03	32:25	0:00	0:01	0:31	1:22	1:43	5:02	25:42
10 AM Discharge Schedule	0:00	0:06	0:58	2:51	3:34	12:29	31:24	0:00	0:00	0:29	1:18	1:40	4:46	25:21
9 AM Discharge Schedule	0:00	0:04	0:51	2:38	3:08	11:29	30:12	0:00	0:00	0:31	1:15	1:27	4:57	24:18
8 AM Discharge Schedule	0:00	0:02	0:49	2:25	2:50	10:36	29:07	0:00	0:00	0:31	1:14	1:26	4:46	23:01
Earlier Intraday Discharges and Just-in-Time Bed Assignments														
11 AM Disch. Sched. + J.i.T.	0:07	0:13	0:18	1:56	1:25	10:32	21:58	0:06	0:11	0:16	0:40	0:20	3:00	19:46
10 AM Disch. Sched. + J.i.T.	0:07	0:12	0:17	1:46	0:50	9:42	21:58	0:06	0:11	0:15	0:37	0:19	2:30	19:46
9 AM Disch. Sched. + J.i.T.	0:07	0:12	0:16	1:34	0:24	9:15	21:58	0:07	0:11	0:15	0:34	0:20	2:03	19:46
8 AM Disch. Sched. + J.i.T.	0:07	0:12	0:16	1:24	0:22	8:32	21:58	0:07	0:12	0:15	0:32	0:20	1:57	19:00
Multi-Day Length of Stay Reductions														
1 Day Earlier	0:00	0:08	1:01	2:52	3:22	13:01	32:40	0:00	0:01	0:36	1:28	1:56	5:51	27:00
2 Days Earlier	0:00	0:03	0:54	2:35	2:54	12:07	29:45	0:00	0:00	0:32	1:20	1:42	5:03	27:00
3 Days Earlier	0:00	0:01	0:48	2:20	2:22	11:18	29:07	0:00	0:01	0:33	1:19	1:36	4:53	27:00
4 Days Earlier	0:00	0:00	0:40	2:07	2:17	10:25	28:53	0:00	0:00	0:32	1:17	1:42	4:35	27:00

Sources: Patcom, Perioperative Case Data, CBEDs, Simulation Results

Notes: Analysis based on ED transfers to neuroscience units between January 1, 2012 and June 30, 2013. Transfers that were in transit for more than 60 minutes after departure from the ED are excluded from comparison. These patients likely went to an unknown intermediate location before they were transferred to Lunder 6, 7, or 8. Hence, bed capacity constraints in the neurosciences might not have been the driving factor of their historical ED wait times. N = 2,247 (ED-to-Lunder 7/8); N = 889 (ED-to-Lunder 6).

Table 11 - Summary of Bed Wait Times for ED Patients Transferring to Neuroscience Units

Wait Times of Surgical Patients Transferring to Neuroscience Units

	Wait Times (hh:mm)									
	Periop-to-Lunder 7/8 Transfers					Periop-to-Lunder 6 Transfers				
Scenario	**Median**	**Mean**	**P75**	**P95**	**Max**	**Median**	**Mean**	**P75**	**P95**	**Max**
Historical Data	0:00	1:38	0:40	12:32	37:25	0:00	0:12	0:00	1:11	18:35
Current State Simulation	0:00	1:37	0:28	13:02	37:25	0:00	0:14	0:00	1:25	18:35
Just-in-Time Bed Assign.	0:00	1:02	0:58	4:24	18:44	0:00	0:24	0:00	2:55	18:29
Earlier Discharges										
11 AM Discharge Schedule	0:00	1:29	0:00	12:52	37:25	0:00	0:12	0:00	1:04	18:17
10 AM Discharge Schedule	0:00	1:22	0:00	12:43	37:25	0:00	0:10	0:00	0:50	18:17
9 AM Discharge Schedule	0:00	1:13	0:00	12:00	36:24	0:00	0:08	0:00	0:28	18:17
8 AM Discharge Schedule	0:00	1:05	0:00	11:29	35:40	0:00	0:07	0:00	0:21	18:17
Earlier Intraday Discharges and Just-in-Time Bed Assignments										
11 AM Disch. Sched. + J.i.T.	0:00	0:50	0:21	3:44	17:36	0:00	0:18	0:00	2:10	17:19
10 AM Disch. Sched. + J.i.T.	0:00	0:41	0:00	3:12	17:36	0:00	0:14	0:00	1:36	16:24
9 AM Disch. Sched. + J.i.T.	0:00	0:32	0:00	2:21	17:36	0:00	0:10	0:00	0:57	15:16
8 AM Disch. Sched. + J.i.T.	0:00	0:26	0:00	1:40	16:43	0:00	0:08	0:00	0:30	14:24
Multi-Day Length of Stay Reductions										
1 Day Earlier	0:00	1:21	0:00	8:39	36:20	0:00	0:12	0:00	1:09	18:17
2 Days Earlier	0:00	1:08	0:00	6:12	26:14	0:00	0:11	0:00	0:52	18:17
3 Days Earlier	0:00	1:00	0:00	5:26	26:14	0:00	0:10	0:00	0:44	18:17
4 Days Earlier	0:00	0:57	0:00	4:59	26:03	0:00	0:09	0:00	0:40	18:17

Sources: Patcom, Perioperative Case Data, CBEDs, Simulation Results

Notes: Analysis based on Periop-to-unit transfers between January 1, 2012 and June 30, 2013. Transfers that were in transit for more than 60 minutes after departure from Periop are excluded from comparison. These patients likely went to an unknown intermediate location before they were transferred to Lunder 6, 7, or 8. Hence, bed capacity constraints in the neurosciences might not have been the driving factor of their historical wait times. N = 1,978 (Periop-to-Lunder 7/8); N = 1,655 (Periop-to-Lunder 6).

Table 12 - Summary of Bed Wait Times for Surgical Patients Transferring to Neuroscience Units

6 Final Recommendations

This section provides recommendations for the implementation of appropriate interventions based on the results from Section 5. It also discusses additional simulations that could supply valuable insights into patient flow dynamics at the hospital and opportunities for process optimization. These simulations can be implemented using the framework and model settings developed in this study.

6.1 Implementation of Process Improvements

We recommend that MGH prioritize the implementation of just-in-time bed assignments over changes to the discharge process in order to reduce bed wait times for ED and surgical patients. Just-in-time bed assignments offer a number of distinct and immediate benefits for both patients and care providers at the hospital. This intervention is also a prerequisite for capturing the full benefits from discharges earlier in the day and multi-day length of stay reductions.

If followed consistently, just-in-time bed assignments can provide significant wait time reductions for patients waiting in the ED and in the perioperative environment for floor beds. As discussed in Section 5.2, average bed wait times for ED-to-Lunder 6 transfers and ED-to-Lunder 7/8 are expected to decrease by 48% and 35%, respectively, at current throughput levels. Similarly, average wait times for surgical patients waiting for beds on Lunder 7 or 8 are expected to decrease by approximately 36%. These benefits are achieved without increasing wait times for unit-to-unit transfers or clinical front door admissions to the neurosciences. Furthermore, the implementation of just-in-time bed assignments decreases the cumulative delay that is unrelated to bed availability (DUBA) during the 18-month period of study from 221 days to 14 days for patients transferring to Lunder 7/8, and from 45 days to eight days for patients transferring to Lunder 6.

The implementation of just-in-time bed assignments is expected to cause less disruption to existing work processes at the hospital than discharges earlier in the day and multi-day length of stay reductions. The transition to just-in-time bed assignments, therefore, probably requires less time and fewer resources than changes to the discharge process.

Importantly, the new bed assignment process can be carried out using the existing IT infrastructure at the hospital. EDIS bed requests could be used to notify bed managers in Admitting about ED patients who are ready for transfer to ICU or floor beds. Similarly, the perioperative data systems already record the time when surgeries are completed, and the time when PACU patients are ready for transfer to an inpatient bed. These timestamps could be used to notify Admitting that ICU and floor patients are ready for transfer, respectively, and should be assigned to clean beds.

At least three important work process adjustments are required to implement just-in-time bed assignments. First, ED staff will have to hold off on bed requests for patients until patients are medically ready for transfer to an inpatient bed. Second, the PACU patient-ready-for-transfer timestamps will have to be recorded more accurately and consistently than is currently the case. Finally, bed managers in Admitting and OAs in the inpatient units will have to assign ICU and floor patients to clean ICU and floor beds, respectively, on a first-ready, first-served basis (with a few appropriate deviations). Beds that are not yet cleaned should not be assigned to patients, and patients who are not yet medically ready for transfer should not yet receive bed assignments.

The consistent implementation of these new procedures is likely the largest challenge since the new work processes may initially seem counterintuitive to stakeholders. Naturally, the ED staff tries to request beds for their patients as early as possible (instead of when the patient is ready for transfer) in order to minimize wait times for patients. Similarly, bed managers and OAs try to make bed-patient assignments as soon as possible instead of just-in-time in order to get through the daily workload faster. Hence, the value of the new work processes will have to be carefully explained to all individuals involved in the bed management process, and adherence to the new work processes will have to be monitored. Without a careful approach, the bed assignment process would likely revert back to its current state over time.

A second issue that will have to be addressed is the handling of surgical patients who require ICU-level care. As discussed in Section 5.2, average wait times in the perioperative environment for these patients increase slightly (i.e., by ten minutes) through just-in-time bed assignments. The number of surgical ICU (i.e., Lunder 6) patients with non-zero bed wait times increases by about 55 patients per year. Hence, more ICU-level patients will have to be accommodated in PACUs before their transfer to Lunder 6 in order to avoid capacity constraints in the ORs. While the additional PACU volume is manageable (i.e., about one additional patient per week), adequate PACU staffing will have to be ensured in order to care for these critically ill patients.

Alternatively, the just-in-time policy could be modified so that critically ill surgical patients can be assigned to beds starting approximately 45 minutes before an OR procedure is expected to finish. This modification would reduce the frequency of post-surgical delays for these patients back to current levels.

While the handling of surgical patients with ICU-level care needs is a foreseeable implementation constraint, additional implementation constraints may arise during pilot testing. The simulation developed in this study can be used to model the impact of these additional constraints and will therefore be instrumental during implementation.

Following the successful implementation of just-in-time bed assignments, discharges earlier in the day and multi-day length of stay reductions can yield further reductions in intraday wait times (see Sections 5.3 and 5.5). Multi-day length of stay reductions can also create capacity for higher patient throughput. These two interventions can be prioritized based on which one is easier to implement. Discharges earlier in the day require care providers to prioritize discharges over other tasks in the morning. This intervention consequently affects the timing of both teaching and patient care activities (e.g., the timing of daily rounds), and disrupts existing workflows in the neuroscience units.

Meanwhile, multi-day length of stay reductions require closer collaboration with capacity-constrained care facilities that MGH frequently discharges patients to. New contracts will have to be negotiated that allow MGH to reserve beds in return for an appropriate fee payment. The analysis of the exact costs associated with discharges earlier in the day and multi-day length of stay reductions is left for future studies.

6.2 Opportunities for Further Study

The patient flow model developed in this study provides several concrete opportunities for further study. First, the existing model can be used to test the effectiveness of additional process interventions. Second, the model can be enhanced using additional data in order to increase its prediction accuracy and versatility. Both approaches have the potential to yield useful insights into patient flow dynamics and quantitative data for the evaluation of process improvement ideas.

Observations of existing work processes at MGH, and interviews with clinicians and administrators can provide interesting ideas for process interventions. Many of these ideas can be simulated by making appropriate modifications to the patient flow model developed in this study. For example, one could analyze the effectiveness of different routing approaches for ED patients who require surgery. While urgent and emergent cases are generally transferred directly from the ED to the OR, non-urgent surgical patients are frequently transferred from the ED to a floor bed, and then transferred from the floor bed to the OR less than 24 hours later. Transferring these patients directly from the ED to the perioperative environment, and accommodating these patients in perioperative bays prior to surgery, could potentially open up significant floor bed capacity and reduce bed wait times for other patients. The patient flow model could be used to quantify resulting wait time reductions and changes in patient volume in the perioperative environment.

In addition, the existing model can be enhanced in a number of meaningful ways. The availability of data currently limits the accuracy of certain aspects of the model. Specifically, wait times for unit-to-unit transfers and front door clinical admissions cannot be calculated accurately. However, additional and more accurate data about these patient populations may become available in the future and could be used to improve the predictions of the model.

Finally, the model can also be expanded to other areas of the hospital. This enhancement would make it possible to analyze the effect of interventions on other clinical specialties at MGH. Expanding the scope of the model would also create opportunities for modeling patient flow issues that reach across clinical specialties. To give one example, one could test approaches for minimizing the number of neuroscience patients who have to be accommodated in other units of the hospital due to capacity constraints in the neuroscience units.

Bibliography

[1] R.B. Bachouch, A. Guinet, and S. Hajri-Gabouj, "Review: An integer linear model for hospital bed planning," *International Journal of Production Economics*, vol. 140, no. 2, 2012, pp. 833–843.

[2] Borghans et al., "Fifty ways to reduce length of stay: An inventory of how hospital staff would reduce the length of stay in their hospital," *Health Policy*, vol. 104, no. 3, 2012, pp. 222–233.

[3] B.A. Christensen, "Improving ICU Patient Flow through Discrete-Event Simulation," master's thesis, Sloan School of Management and Engineering Systems Division, Massachusetts Institute of Technology, 2012.

[4] J.E. Gentle, *Computational Statistics*, Springer, 2009.

[5] R.M. Graue, "Prediction and Optimization Techniques to Streamline Surgical Scheduling," master's thesis, Sloan School of Management and Department of Aeronautics and Astronautics, Massachusetts Institute of Technology, 2013.

[6] P. Hendy et al., "In-depth analysis of delays to patient discharge: a metropolitan teaching hospital experience," *Clinical Medicine*, vol. 12, no. 4, 2012, pp. 320–323.

[7] M.U. Majeed et al., "Delay in discharge and its impact on unnecessary hospital bed occupancy," *BMC Health Services Research*, vol. 12, no. 1, 2012, pp. 410–415.

[8] J.H. McDonald, *Handbook of Biological Statistics*, Sparky House Publishing, 2nd ed., 2009.

[9] E.S. Powell et al., "The Relationship between Inpatient Discharge Timing and Emergency Department Boarding," *Journal of Emergency Medicine*, vol. 42, no. 2, 2012, pp. 186–196.

[10] D.J. Price, "Managing Variability to Improve Quality, Capacity and Cost in the Perioperative Process at Massachusetts General Hospital," master's thesis, Sloan School of Management and Engineering Systems Division, Massachusetts Institute of Technology, 2011.

[11] A.R. Range, "Improving Surgical Patient Flow through Simulation of Scheduling Heuristics," master's thesis, Sloan School of Management and Engineering Systems Division, Massachusetts Institute of Technology, 2013.

[12] J.D. Sattler et al., "Bed management in intensive care – Prospective research into the organizational influences on intensive care bed allocation," *Anästhesiologie & Intensivmedizin*, vol. 54, 2013, pp. 225–232.

[13] R. Schmidt, S. Geisler, and C. Spreckelsen, "Decision support for hospital bed management using adaptable individual length of stay estimations and shared resources," *BMC Medical Informatics And Decision Making*, vol. 13, 2013

[14] T.A. Schwartz, "Improving Surgical Patient Flow in a Congested Recovery Area," master's thesis, Sloan School of Management and Department of Mechanical Engineering, Massachusetts Institute of Technology, 2012.

[15] B.G. Thomas, "Automated Bed Assignments in a Complex and Dynamic Hospital Environment," *Interfaces*, vol. 43, no. 5, 2013, pp. 435–448.

Appendix A – Calculation of Bed Wait Times for Patients Transferring to Neuroscience Units

As shown in Appendix B, the patient flow model consists of the following modules:

1) Emergency Department
2) Perioperative Environment
3) Inpatient Bed Units
    a. Neuroscience Inpatient Units (Lunder 6 ICU, and Lunder 7 and 8 Floors)
    b. Overflow Inpatient Units (non-neuroscience ICUs and Floors)

Only the neuroscience units in the model are explicitly capacity constrained, meaning that the model at any given time does not allow for more than 22 patients in the Lunder 6 ICU or 64 patients on the Lunder 7 and 8 Floors combined. The time at which the next patient can be transferred to a neuroscience unit consequently depends on the unit's current occupancy and/or the departure times of patients who are currently in the unit.

We can illustrate this point using two hypothetical patients who need to be transferred to Lunder 6. The first patient is currently in the ED while the second patient is in the OR. Assume that Lunder 6 is currently at capacity with 22 patients. In order to accommodate another patient, one of these 22 occupants consequently has to depart from Lunder 6 and that occupant's bed has to be cleaned. The time of the next patient departure and the duration of the subsequent cleaning are known since they are recorded in the Patcom and CBEDs datasets, respectively. Admitting is notified of the bed that is (or is going to become) available and the relevant bed manager then has to decide which patient she is going to assign the bed to (i.e., the bed manager has to prioritize one patient over the other).[34]

We can infer the relative priority that was given historically to each individual patient from the Patcom and CBEDs datasets. First, Patcom records the exact bed that every patient was transferred to on Lunder 6.

[34] For a general discussion of the bed assignment process in Admitting, see Section 3.3.

For example, we might know that the ED patient ultimately went to bed L06-24-A while the OR patient went to bed L06-30-A. This allows us to determine when the bed that the patient went to was last cleaned prior to the patient's arrival. By comparing the two bed clean timestamps, we can then determine which patient was prioritized by Admitting. For example, if the bed cleaning of L06-24-A was completed at 10:08 AM and the bed cleaning of L06-30-A was completed at 11:30 AM (on the same day), we know that the bed that became available in the simulation should be assigned to the ED patient instead of the OR patient.

Prior to the start of the simulation, we rank all patient transfers to Lunder 6 (from the ED, the OR, other inpatient units, etc.) in the historical data using this method. This process is shown in Table 13. Whenever a Lunder 6 bed becomes available in the simulation, we then use the ranking to determine the recipient of the bed. The patient with the lowest ranking who has not yet received a bed is going to receive it.

Patient Identifier	**Transfer Origin**	**Bed Patient Transferred to Historically** *(Patcom)*	**Historical Transfer Time** *(Patcom)*	**Completion of Last Bed Cleaning Prior to Transfer** *(CBEDs)*	**Implied Transfer Ranking**
Patient X	ED	L06-12A	2011/9/15 10:13 AM	2011/9/15 6:25 AM	1
Patient Y	OR	L06-60A	2011/9/15 8:10 AM	2011/9/15 7:30 AM	2
Patient A	Overflow ICU	L06-24A	2011/9/15 5:27 PM	2011/9/15 3:15 PM	3
Patient D	OR	L06-10A	2011/9/15 4:10 PM	2011/9/15 3:45 PM	4
⋮	⋮	⋮	⋮	⋮	⋮
Patient Y	Lunder 7/8	L06-62A	2011/9/27 4:10 PM	2011/9/27 1:51 PM	29
⋮	⋮	⋮	⋮	⋮	⋮
Patient G	Front Door	L06-24A	2013/6/30 9:34 PM	2013/6/30 2:21 PM	3,221
⋮	⋮	⋮	⋮	⋮	⋮

Table 13 - Priority Ranking of Patient Transfers to Lunder 6

Patients who transferred to Lunder 6 several times during their stay at MGH will receive a unique ranking for each transfer. In the example above this is the case for Patient Y. She was transferred to Lunder 6 for the first time from the OR on September 15, 2011. From there she was transferred to Lunder 7/8. (This is implied by the information in the table but not shown explicitly.) On September, 27, 2011, this patient was transferred back to Lunder 6. The second transfer has a separate ranking (29) from the same patient's first transfer (2) since the patient had to wait for a new bed to become available in the ICU.

Patients returning from the OR to the bed that they occupied before their surgery are exempt from this rule (e.g., a patient being transferred from L06-64A to the OR, and subsequently back to L06-64A). These patients just receive a transfer ranking for their original admission to Lunder 6. When these patients go to the OR, their beds are held and not given to another patient. This reality is incorporated in the simulation and these patients consequently do not incur bed waits after their surgeries.

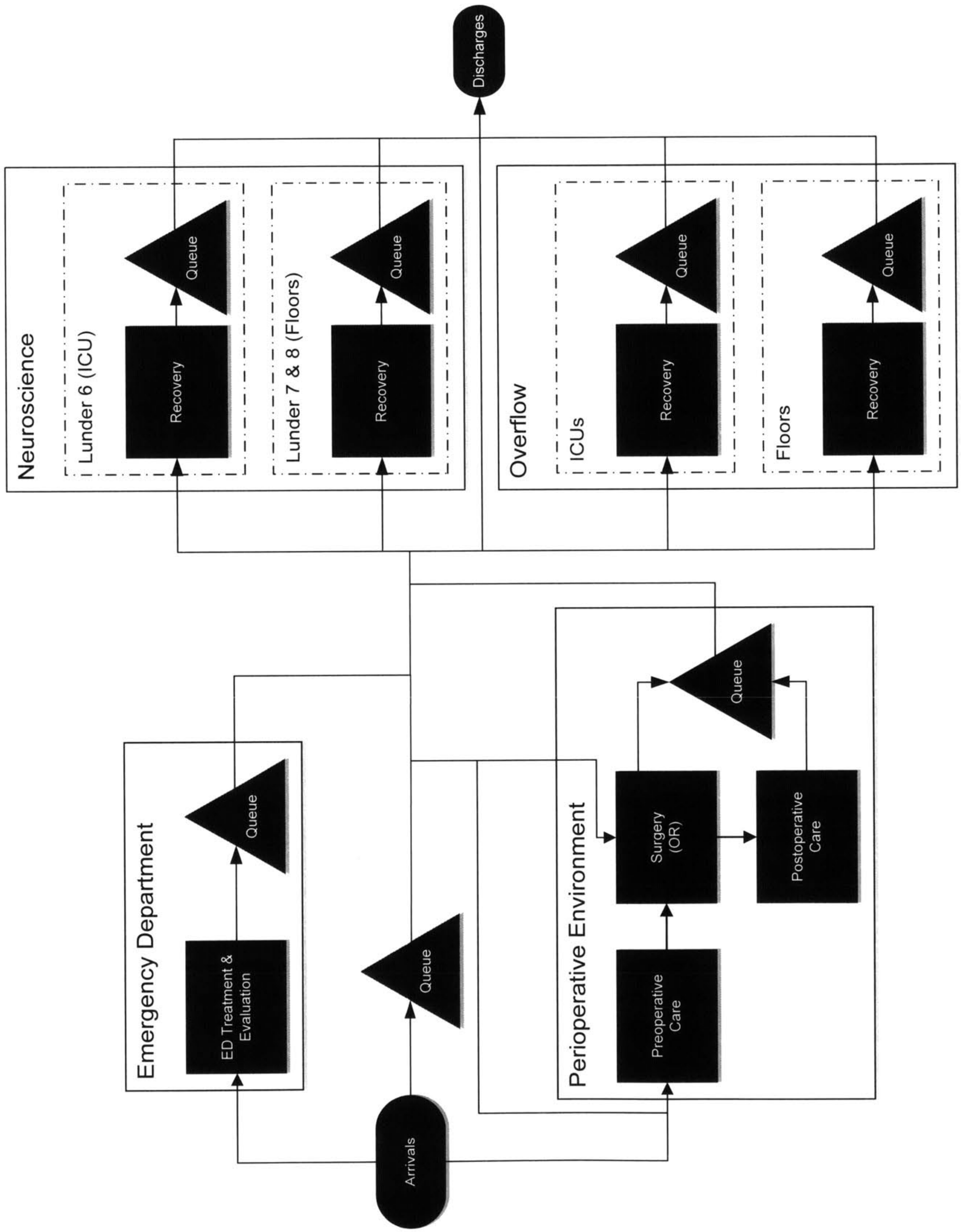
Note that the ranking in Table 13 is not based on patients' medical readiness for transfer. The simulation therefore incorporates scenarios like the one depicted in Figure 2. If a bed on Lunder 6 becomes available but the patient with the next lowest transfer ranking is not yet medically ready for transfer (e.g., she is still being treated in the ED), then the bed will be held for that patient even though other patients in the hospital may be medically ready to transfer to Lunder 6.

While this example focuses on Lunder 6, an equivalent process is carried out for all patient transfers to the 64 neuroscience floor beds on Lunder 7 and 8. In aggregate, the simulation logs 3,221 ranked transfers to Lunder 6 and 9,428 ranked transfers to Lunder 7 and 8 before July 1, 2013.

Since the other modules in the simulation (i.e., the OR, the ED, and the overflow units) are not explicitly capacity constrained, no ranking is required for patients who were transferred to these destinations.[35] The transfer times of these patients are taken from the historical data and unaffected by the different process interventions.

[35] These destinations are still implicitly capacity constrained. Capacity constraints in these units affect the historical transfer times of patients going to these units. Since these transfer times are taken as an input to the model, constraints in these units are implicitly considered.

Appendix B – Patient Flow Model



Appendix C – Simulation Summary Statistics

Statistic	
Time Period Covered by Data	September 1, 2011 – July 1 2013
Total Admissions	9,946
Through ED	*5,103*
Through Periop	*2,900*
To Lunder 6	*188*
To Lunder 7/8	*1,504*
To Overflow ICUs	*14*
To Overflow Floors	*222*
Total Discharges[36]	9,945
From ED	*0*
From Periop	*43*
From Lunder 6	*474*
From Lunder 7/8	*8,475*
From Overflow ICUs	*286*
From Overflow Floors	*667*
ED Visits	5,103
Surgeries	5,315
Preop	*4,211*
PACU	*2,818*
Lunder 6 Visits	3,702
Lunder 7, 8 Visits	10,066
Overflow ICU Visits	851
Overflow Floor Visits	1,636
ED-to-Periop Transfers	328
ED-to-Lunder 6 Transfers	1,138
ED-to-Lunder 7/8 Transfers	2,784
ED-to-Overflow ICU Transfers	161
ED-to-Overflow Floor Transfers	692
Periop-to-Lunder 6 Transfers	1,999

[36] Discharge figures include patient expirations.

Periop-to-Lunder 7/8 Transfers	2,351
Periop-to-Overflow ICU Transfers	545
Periop-to-Overflow Floor Transfers	377
Lunder 6-to-Periop Transfers	542
Lunder 6-to-Lunder 7/8 Transfers	2,536
Lunder 6-to-Overflow ICU Transfers	19
Lunder 6-to-Overflow Floor Transfers	131
Lunder 7/8-to-Periop Transfers	1,220
Lunder 7/8-to-Lunder 6 Transfers	220
Lunder 7/8-to-Overflow ICU Transfers	61
Lunder 7/8-to-Overflow Floor Transfers	90
Overflow ICU-to-Periop Transfers	72
Overflow ICU-to-Lunder 6 Transfers	73
Overflow ICU-to-Lunder 7/8 Transfers	315
Overflow ICU-to-Overflow Floor Transfers	105
Overflow Floor-to-Periop Transfers	247
Overflow Floor-to-Lunder 6 Transfers	84
Overflow Floor-to-Lunder 7/8 Transfers	571
Overflow Floor-to-Overflow ICU Transfers	51
Number of Transfers per Patient (excl. Admission and Discharge)	Min: 1; Median: 2; Mean: 2.86; Max: 24

Appendix D – Estimation of Patients' Medical Readiness for Transfer

Estimation of Patients' Medical Readiness for Transfer (ED Patients)

Patient Population *(Source Dataset)*

ED-to-Lunder 7/8, ED-to-Lunder 6, ED-to-Overflow Floor, and ED-to-Overflow ICU Transfers *(EDIS)*

```
MIN(U[Bed Request Time, MIN(ED Departure Time, Nurse Handoff Time,
      MD Handoff Time)], ED Arrival Time + 12 Hours)
```

ED-to-Periop Transfers *(EDIS, Perioperative Case Data)*

```
MIN(Case Booking Time, ED Departure Time)
```

Notes: `U[A,B]` indicates a random sample from the uniform distribution between A and B with $A \leq B$.

Table 14 - Estimation of Patients' Medical Readiness for Transfer (ED Patients)

Estimation of Patients' Medical Readiness for Transfer (Perioperative Patients)

Patient Population *(Source Dataset)*

PACU-to-Lunder 7/8 and PACU-to-Overflow Floor Transfers *(Perioperative Data)*

```
Ready to Depart PACU Time
```

OR-to-Lunder 6, OR-to-Lunder 7/8, PACU-to-Lunder 6, OR-to-Overflow ICU, OR-to-Overflow Floor, and PACU-to-Overflow ICU Transfers *(Perioperative Data)*

```
Completion of Surgery Time
```

Table 15 - Estimation of Patients' Medical Readiness for Transfer (Perioperative Patients)

Estimation of Patients' Medical Readiness for Transfer (Inpatient Units)

Patient Population *(Source Dataset)*

Overflow Floor-to-Lunder 7/8, Lunder 6-to-Lunder 7/8, Overflow ICU-to-Lunder 7/8, and Overflow ICU-to-Lunder 6 Transfers *(Patcom)*

If historical transfer time between 5 PM Day 1 and 9 AM Day 2:

```
U[MAX(Pt Arrival Time in Preceding Location, 5 PM Day 1), Pt Arrival Time]
```

Else if historical transfer time between 9 AM and 5 PM:

```
U[MAX(Pt Arrival Time in Preceding Location, 9 AM), Pt Arrival Time]
```

Overflow Floor-to-Lunder 6 and Lunder 7/8-to-Lunder 6 Transfers *(Patcom)*

If historical transfer time before 9 AM:

```
T[MAX(Pt Arrival Time in Preceding Location, 5 PM Previous Day), Pt Arrival Time]
```

Else:

```
T[MAX(Pt Arrival Time in Preceding Location, 9 AM Same Day), Pt Arrival Time]
```

Front Door-to-Lunder 6 and Front Door-to-Lunder 7/8 Transfers *(Patcom)*

```
MIN(Admission Time, Pt Arrival Time)
```

Table 16 - Estimation of Patients' Medical Readiness for Transfer (Inpatient Units)

Estimation of Patients' Medical Readiness for Transfer (Patients Transferring to Neuroscience Units)

Patient Population *(Source Dataset)*

ED-to-Lunder 7/8 and ED-to-Lunder 6 Transfers *(EDIS)*

```
MIN(U[Bed Request Time, MIN(ED Departure Time, Nurse Handoff Time,
      MD Handoff Time)], ED Arrival Time + 12 Hours)
```

PACU-to-Lunder 7/8 Transfers *(Perioperative Data)*

```
Ready to Depart PACU Time
```

OR-to-Lunder 6, OR-to-Lunder 7/8, and PACU-to-Lunder 6 Transfers *(Perioperative Data)*

```
Completion of Surgery Time
```

Overflow Floor-to-Lunder 7/8, Lunder 6-to-Lunder 7/8, Overflow ICU-to-Lunder 7/8, and Overflow ICU-to-Lunder 6 Transfers *(Patcom)*

If historical transfer time between 5 PM Day 1 and 9 AM Day 2:

```
U[MAX(Pt Arrival Time in Preceding Location, 5 PM Day 1), Pt Arrival Time]
```

Else if historical transfer time between 9 AM and 5 PM:

```
U[MAX(Pt Arrival Time in Preceding Location, 9 AM), Pt Arrival Time]
```

Overflow Floor-to-Lunder 6 and Lunder 7/8-to-Lunder 6 Transfers *(Patcom)*

If historical transfer time before 9 AM:

```
T[MAX(Pt Arrival Time in Preceding Location, 5 PM Previous Day), Pt Arrival Time]
```

Else:

```
T[MAX(Pt Arrival Time in Preceding Location, 9 AM Same Day), Pt Arrival Time]
```

Front Door-to-Lunder 6 and Front Door-to-Lunder 7/8 Transfers *(Patcom)*

```
MIN(Admission Time, Pt Arrival Time)
```

Notes: `U[A,B]` indicates a random sample from the uniform distribution between A and B with $A \leq B$. `T[A,B]` indicates a random sample from the triangular distribution between A and B with $A \leq B$. The peak of the triangle is at B. The triangular distribution is implemented to capture the fact that floor-to-ICU transfers mostly happen due to unexpected deteriorations in patients' conditions. These patients often require a quick transfer to an ICU and the hospital handles these patients accordingly. Hence, these patients tend to be "medically ready" closer to their historical transfer time than other unit-to-unit transfer patients.

Table 17 - Estimation of Patients' Medical Readiness for Transfer (Patients Transferring to Neuroscience Units)

Appendix E – Differences between Historical Data and Current State Simulation

This appendix provides a discussion of differences between the current state patient flow simulation and the historical data. Each section addresses the reason for the difference and the expected bias (if any) that it introduces into the simulation results.

Lack of Historical Data about Bed Closings

Individual beds at MGH are occasionally closed (i.e., declared unavailable) for an extended time. These bed closings can occur for a variety of reasons, including staffing shortages, repairs, and maintenance.[37] Bed closings are not tracked in the available historical data even though they directly limit the available bed capacity. Due to the lack of data, bed closings are not reflected in the model even though they may have occurred occasionally during the period of study. This could potentially cause simulated wait times to be slightly lower than historical wait times.

Inaccuracies in CBEDs Bed Cleaning Data

Despite extensive data cleaning, the limited quality of the CBEDs bed cleaning data is another factor that might cause differences between the historical data calculations and the baseline model results. For example, in certain cases the data indicate that a bed was cleaned more than once between two consecutive bed occupants (i.e., patients). Due to missing timestamps in the different observations, it is not always possible to determine if these seemingly redundant cleanings represent distinct cleanings that actually occurred, or the same cleaning that was recorded multiple times.

Multiple cleanings might have occurred for valid reasons. First, the bed might have been closed between the two cleanings. If the closing was due to repair, it may have been necessary to re-clean the bed after the repair was completed. Second, there may have been an actual patient in the bed for a very short time

[37] In units with shared rooms, bed closings also occur for a variety of other reasons (e.g., infectious or disruptive patients who cannot be matched with roommates). However, these issues do not apply to the neuroscience ICU and floors since these units feature only individual rooms. The frequency of bed closings is therefore greatly reduced in these units.

between the two cleanings. As discussed in Section 4.2.3, we remove patient stays in individual beds that are shorter than one hour since these instances frequently indicate data entry errors, and do not reflect actual patient transfers. However, in a limited number of instances these short bed occupancies might have actually occurred and necessitated an additional bed cleaning that is not considered in the model.

As outlined in Appendix A, the model only considers the first cleaning after a patient's departure from a bed. After that cleaning is completed, the bed is considered ready for occupancy by the next patient. The historical data calculations of bed wait times on the other hand rely on the last cleaning of a bed that was completed before a waiting patient was transferred to that bed. In cases with multiple bed cleanings between two consecutive bed occupants, this would be a different cleaning than what is considered in the simulation. Hence, this issue may cause historical wait times to be slightly longer in some instances than simulated wait times.

Intra-Unit Patient Transfers

As discussed in Section 4.2.3, the baseline simulation does not consider patients transfers within the two neuroscience floors and within the neuroscience ICU, respectively. This approach allows us to simulate capacity constraints in the neurosciences without having to consider all 86 beds as separate locations in the hospital. In other words, the simulation enforces overall capacity constraints for Lunder 7/8 and Lunder 6, respectively, without considering which beds on the units are currently occupied and which are free.

In reality, some intra-unit transfers do occur, but they are relatively rare (about 5% of all transfers). A patient might for example be moved from one bed on Lunder 7 to another bed on the same floor in order to have patients who are cared for by the same nurse be located in adjacent rooms. These intra-unit transfers generate additional bed cleanings (and therefore capacity constraints) that are not tracked in the simulation. Just like the preceding two issues, this might cause historical wait times to be slightly longer than modeled wait times.

Sampled Bed Assignment Times

The bed assignment durations of ED patients in the simulation are sampled from distributions that depend on the patients' bed cleaning durations. See Section 4.3.1 for a detailed discussion. This sampling is done in order to capture the strong correlation between bed cleaning durations and bed assignment durations. While this is necessary in order to model different interventions accurately, it also implies that the baseline model bed assignment wait of any given patient does not necessarily reflect her actual bed assignment wait in the historical data. Although this issue should not produce a systematic offset between the historical and simulated wait times, it does introduce random differences.

Appendix F – Model Results

Bed Wait Time Statistics
Comparison of Historical Data, Current State Model, and Intervention Models
Emergency Department-to-Neuroscience Transfers

ED-to-Lunder 7/8 Transfers

	Historical Data	Current State Simulation	Just-in-Time Bed Assignments	Earlier Discharges: 11 AM Discharge Schedule	Earlier Discharges: 10 AM Discharge Schedule	Earlier Discharges: 9 AM Discharge Schedule	Earlier Discharges: 8 AM Discharge Schedule	Earlier Discharges and Just-in-Time Bed Assignments: 11 AM Disch. Schedule + J.i.T.	Earlier Discharges and Just-in-Time Bed Assignments: 10 AM Disch. Schedule + J.i.T.	Earlier Discharges and Just-in-Time Bed Assignments: 9 AM Disch. Schedule + J.i.T.	Earlier Discharges and Just-in-Time Bed Assignments: 8 AM Disch. Schedule + J.i.T.	Length of Stay Reductions: 1 Day Earlier	Length of Stay Reductions: 2 Days Earlier	Length of Stay Reductions: 3 Days Earlier	Length of Stay Reductions: 4 Days Earlier
Wait Length Frequencies (# of Patients)															
0 Min	238	415	2	469	483	524	545	1	4	4	3	470	530	556	624
> 0 Min	2,009	1,832	2,245	1,778	1,764	1,723	1,702	2,246	2,243	2,243	2,244	1,777	1,717	1,691	1,623
> 30 Min	1,520	1,480	797	1,406	1,385	1,341	1,321	673	596	512	455	1,416	1,355	1,301	1,227
> 60 Min	1,207	1,211	711	1,128	1,102	1,046	1,023	606	543	474	415	1,127	1,068	987	925
> 120 Min	838	859	561	788	765	723	691	499	455	411	373	774	723	645	618
> 180 Min	644	663	458	626	601	575	540	428	399	367	338	598	541	468	438
> 240 Min	549	561	395	537	520	484	460	371	355	324	294	489	448	393	358
Wait Time Summary Statistics (hh:mm)															
Min	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00
P5	0:00	0:00	0:07	0:00	0:00	0:00	0:00	0:07	0:07	0:07	0:07	0:00	0:00	0:00	0:00
P25	0:18	0:13	0:13	0:07	0:06	0:04	0:02	0:13	0:12	0:12	0:12	0:08	0:03	0:01	0:00
Median	1:10	1:12	0:18	1:01	0:58	0:51	0:49	0:18	0:17	0:16	0:16	1:01	0:54	0:48	0:40
P75	3:54	4:00	2:00	3:43	3:34	3:08	2:50	1:25	0:50	0:24	0:22	3:22	2:54	2:22	2:17
P95	13:47	13:51	10:47	13:03	12:29	11:29	10:36	10:32	9:42	9:15	8:32	13:01	12:07	11:18	10:25
Max	34:00	34:00	21:58	32:25	31:24	30:12	29:07	21:58	21:58	21:58	21:58	32:40	29:45	29:07	28:53
Mean	3:14	3:15	2:07	3:01	2:51	2:38	2:25	1:56	1:46	1:34	1:24	2:52	2:35	2:20	2:07
St. Dev.	4:41	4:42	3:40	4:30	4:18	4:02	3:45	3:32	3:22	3:07	2:52	4:24	4:07	3:54	3:40
N	2,247	2,247	2,247	2,247	2,247	2,247	2,247	2,247	2,247	2,247	2,247	2,247	2,247	2,247	2,247

ED-to-Lunder 6 Transfers

	Historical Data	Current State Simulation	Just-in-Time Bed Assignments	Earlier Discharges: 11 AM Discharge Schedule	Earlier Discharges: 10 AM Discharge Schedule	Earlier Discharges: 9 AM Discharge Schedule	Earlier Discharges: 8 AM Discharge Schedule	Earlier Discharges and Just-in-Time Bed Assignments: 11 AM Disch. Schedule + J.i.T.	Earlier Discharges and Just-in-Time Bed Assignments: 10 AM Disch. Schedule + J.i.T.	Earlier Discharges and Just-in-Time Bed Assignments: 9 AM Disch. Schedule + J.i.T.	Earlier Discharges and Just-in-Time Bed Assignments: 8 AM Disch. Schedule + J.i.T.	Length of Stay Reductions: 1 Day Earlier	Length of Stay Reductions: 2 Days Earlier	Length of Stay Reductions: 3 Days Earlier	Length of Stay Reductions: 4 Days Earlier
Wait Length Frequencies (# of Patients)															
0 Min	129	199	1	220	226	234	239	3	1	1	2	222	230	220	233
> 0 Min	760	690	888	669	663	655	650	886	888	888	887	667	659	669	656
> 30 Min	499	489	140	453	441	450	446	116	106	93	81	473	450	464	449
> 60 Min	364	338	115	322	309	301	293	94	85	71	62	350	324	319	309
> 120 Min	199	203	85	192	185	170	163	68	55	45	41	212	187	178	187
> 180 Min	121	130	57	126	114	110	108	45	37	35	30	128	120	114	110
> 240 Min	71	79	37	66	59	69	63	31	29	24	21	71	65	64	64
Wait Time Summary Statistics (hh:mm)															
Min	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00
P5	0:00	0:00	0:07	0:00	0:00	0:00	0:00	0:06	0:06	0:07	0:07	0:00	0:00	0:00	0:00
P25	0:09	0:04	0:12	0:01	0:00	0:00	0:00	0:11	0:11	0:11	0:12	0:01	0:00	0:01	0:00
Median	0:39	0:37	0:15	0:31	0:29	0:31	0:31	0:16	0:15	0:15	0:15	0:36	0:32	0:33	0:32
P75	1:47	1:49	0:21	1:43	1:40	1:27	1:26	0:20	0:19	0:20	0:20	1:56	1:42	1:36	1:42
P95	5:10	5:49	3:37	5:02	4:46	4:57	4:46	3:00	2:30	2:03	1:57	5:51	5:03	4:53	4:35
Max	20:45	27:00	19:46	25:42	25:21	24:18	23:01	19:46	19:46	19:46	19:00	27:00	27:00	27:00	27:00
Mean	1:23	1:27	0:45	1:22	1:18	1:15	1:14	0:40	0:37	0:34	0:32	1:28	1:20	1:19	1:17
St. Dev.	1:58	2:26	1:48	2:23	2:18	2:13	2:11	1:39	1:34	1:28	1:22	2:28	2:20	2:19	2:12
N	889	889	889	889	889	889	889	889	889	889	889	889	889	889	889

Sources: Patcom, Perioperative Case Data, EDIS, CBEDs, Simulation Results

Notes: Analysis based on ED-to-unit transfers between January 1, 2012 and June 30, 2013. Transfers that were in transit for more than 60 minutes after their departure from the ED are excluded from comparison. These patients likely went to an unknown intermediate location before being transferred to Lunder 6, 7, or 8. Hence, bed capacity constraints in the neurosciences might not have been the driving factor of their historical ED wait times.

Bed Wait Time Statistics
Comparison of Historical Data, Current State Model, and Intervention Models
Periop-to-Neuroscience Transfers

Periop-to-Lunder 7/8 Transfers

				Earlier Discharges				Earlier Discharges and Just-in-Time Bed Assignments				Length of Stay Reductions			
	Historical Data	Current State Simulation	Just-in-Time Bed Assignments	11 AM Discharge Schedule	10 AM Discharge Schedule	9 AM Discharge Schedule	8 AM Discharge Schedule	11 AM Disch. Schedule + J.i.T.	10 AM Disch. Schedule + J.i.T.	9 AM Disch. Schedule + J.i.T.	8 AM Disch. Schedule + J.i.T.	1 Day Earlier	2 Days Earlier	3 Days Earlier	4 Days Earlier
Wait Length Frequencies (# of Patients)															
0 Min	1,357	1,402	1,238	1,496	1,569	1,651	1,720	1,385	1,528	1,664	1,800	1,492	1,555	1,602	1,637
> 0 Min	621	576	740	482	409	327	258	593	450	314	178	486	423	376	341
> 30 Min	525	490	607	419	354	284	225	462	350	232	136	410	358	318	285
> 60 Min	438	416	485	357	309	249	205	368	276	170	118	357	305	276	250
> 120 Min	320	321	303	275	242	204	177	214	149	115	92	277	241	213	190
> 180 Min	255	255	198	215	193	172	156	133	106	89	77	215	176	147	132
> 240 Min	203	196	118	176	162	149	144	93	84	74	64	160	133	118	112
Wait Time Summary Statistics (hh:mm)															
Min	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00
P5	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00
P25	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00
Median	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00
P75	0:40	0:28	0:58	0:00	0:00	0:00	0:00	0:21	0:00	0:00	0:00	0:00	0:00	0:00	0:00
P95	12:32	13:02	4:24	12:52	12:43	12:00	11:29	3:44	3:12	2:21	1:40	8:39	6:12	5:26	4:59
Max	37:25	37:25	18:44	37:25	37:25	36:24	35:40	17:36	17:36	17:36	16:43	36:20	26:14	26:14	26:03
Mean	1:38	1:37	1:02	1:29	1:22	1:13	1:05	0:50	0:41	0:32	0:26	1:21	1:08	1:00	0:57
St. Dev.	4:33	4:35	2:34	4:29	4:20	4:08	3:56	2:27	2:21	2:13	2:04	4:12	3:49	3:36	3:32
N	1,978	1,978	1,978	1,978	1,978	1,978	1,978	1,978	1,978	1,978	1,978	1,978	1,978	1,978	1,978

Periop-to-Lunder 6 Transfers

				Earlier Discharges				Earlier Discharges and Just-in-Time Bed Assignments				Length of Stay Reductions			
	Historical Data	Current State Simulation	Just-in-Time Bed Assignments	11 AM Discharge Schedule	10 AM Discharge Schedule	9 AM Discharge Schedule	8 AM Discharge Schedule	11 AM Disch. Schedule + J.i.T.	10 AM Disch. Schedule + J.i.T.	9 AM Disch. Schedule + J.i.T.	8 AM Disch. Schedule + J.i.T.	1 Day Earlier	2 Days Earlier	3 Days Earlier	4 Days Earlier
Wait Length Frequencies (# of Patients)															
0 Min	1,436	1,441	1,358	1,480	1,506	1,531	1,547	1,427	1,466	1,500	1,534	1,474	1,492	1,507	1,516
> 0 Min	219	214	297	175	149	124	108	228	189	155	121	181	163	148	139
> 30 Min	145	148	235	117	101	80	69	184	153	117	82	126	110	97	93
> 60 Min	97	105	190	91	71	60	50	149	124	79	61	91	73	65	62
> 120 Min	46	62	131	53	43	34	28	97	58	43	30	50	42	40	39
> 180 Min	30	41	78	35	25	20	17	49	32	21	16	34	28	27	26
> 240 Min	16	24	43	20	15	14	12	29	20	18	11	20	18	18	18
Wait Time Summary Statistics (hh:mm)															
Min	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00
P5	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00
P25	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00
Median	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00
P75	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00
P95	1:11	1:25	2:55	1:04	0:50	0:28	0:21	2:10	1:36	0:57	0:30	1:09	0:52	0:44	0:40
Max	18:35	18:35	18:29	18:17	18:17	18:17	18:17	17:19	16:24	15:16	14:24	18:17	18:17	18:17	18:17
Mean	0:12	0:14	0:24	0:12	0:10	0:08	0:07	0:18	0:14	0:10	0:08	0:12	0:11	0:10	0:09
St. Dev.	0:53	1:04	1:21	1:00	0:57	0:53	0:50	1:10	1:02	0:54	0:48	1:01	0:58	0:56	0:56
N	1,655	1,655	1,655	1,655	1,655	1,655	1,655	1,655	1,655	1,655	1,655	1,655	1,655	1,655	1,655

Sources: Patcom, Perioperative Case Data, EDIS, CBEDs, Simulation Results

Notes: Analysis based on Periop-to-unit transfers between January 1, 2012 and June 30, 2013. Transfers that were in transit for more than 60 minutes after their departure from Periop are excluded from comparison. These patients likely went to an unknown intermediate location before being transferred to Lunder 6, 7, or 8. Hence, bed capacity constraints in the neurosciences might not have been the driving factor of their historical wait times.

Bed Wait Time Statistics
Comparison of Historical Data, Current State Model, and Intervention Models
Floor-to-Neuroscience Transfers

Floor-to-Lunder 7/8 Transfers

				Earlier Discharges				Earlier Discharges and Just-in-Time Bed Assignments				Length of Stay Reductions			
	Historical Data	Current State Simulation	Just-in-Time Bed Assignments	11 AM Discharge Schedule	10 AM Discharge Schedule	9 AM Discharge Schedule	8 AM Discharge Schedule	11 AM Disch. Schedule + J.i.T.	10 AM Disch. Schedule + J.i.T.	9 AM Disch. Schedule + J.i.T.	8 AM Disch. Schedule + J.i.T.	1 Day Earlier	2 Days Earlier	3 Days Earlier	4 Days Earlier
Wait Length Frequencies (# of Patients)															
0 Min	202	237	229	252	274	321	372	252	274	321	372	259	282	301	326
> 0 Min	261	226	234	211	189	142	91	211	189	142	91	204	181	162	137
> 30 Min	238	207	216	195	163	115	59	195	163	115	59	182	164	147	121
> 60 Min	212	185	189	169	138	88	41	169	138	88	41	166	146	130	106
> 120 Min	159	135	126	105	74	40	22	105	74	40	22	119	113	100	80
> 180 Min	124	106	86	67	38	21	12	67	38	21	12	90	76	68	53
> 240 Min	76	67	47	24	15	7	5	24	15	7	5	55	46	41	34
Wait Time Summary Statistics (hh:mm)															
Min	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00
P5	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00
P25	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00
Median	0:35	0:00	0:04	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00
P75	3:12	2:43	2:14	1:54	1:21	0:29	0:00	1:54	1:21	0:29	0:00	2:12	1:46	1:20	0:42
P95	6:26	6:28	5:08	4:01	3:33	2:51	1:45	4:01	3:33	2:51	1:45	6:06	5:30	5:03	4:33
Max	10:09	17:54	15:02	15:02	15:02	14:24	12:46	15:02	15:02	14:24	12:46	10:15	9:59	9:55	9:55
Mean	1:44	1:33	1:21	1:06	0:51	0:33	0:19	1:06	0:51	0:33	0:19	1:19	1:09	0:59	0:48
St. Dev.	2:16	2:20	2:00	1:48	1:38	1:25	1:12	1:48	1:38	1:25	1:12	2:05	1:57	1:47	1:39
N	463	463	463	463	463	463	463	463	463	463	463	463	463	463	463

Floor-to-Lunder 6 Transfers

				Earlier Discharges				Earlier Discharges and Just-in-Time Bed Assignments				Length of Stay Reductions			
	Historical Data	Current State Simulation	Just-in-Time Bed Assignments	11 AM Discharge Schedule	10 AM Discharge Schedule	9 AM Discharge Schedule	8 AM Discharge Schedule	11 AM Disch. Schedule + J.i.T.	10 AM Disch. Schedule + J.i.T.	9 AM Disch. Schedule + J.i.T.	8 AM Disch. Schedule + J.i.T.	1 Day Earlier	2 Days Earlier	3 Days Earlier	4 Days Earlier
Wait Length Frequencies (# of Patients)															
0 Min	148	156	175	161	166	169	179	185	188	193	198	162	164	164	168
> 0 Min	79	71	52	66	61	58	48	42	39	34	29	65	63	63	59
> 30 Min	72	64	46	58	52	43	39	40	35	27	24	58	56	55	51
> 60 Min	60	52	41	48	44	38	35	35	31	26	20	49	46	45	43
> 120 Min	40	38	26	33	29	24	21	24	20	15	13	32	32	31	26
> 180 Min	32	27	20	23	21	17	16	14	11	8	8	25	22	21	21
> 240 Min	25	21	13	16	16	14	13	11	8	8	6	17	16	16	16
Wait Time Summary Statistics (hh:mm)															
Min	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00
P5	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00
P25	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00
Median	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00
P75	1:17	0:50	0:00	0:32	0:15	0:02	0:00	0:00	0:00	0:00	0:00	0:34	0:25	0:25	0:16
P95	5:40	5:39	4:04	5:15	4:55	4:55	4:55	3:24	2:58	2:33	2:07	5:24	5:06	4:59	4:59
Max	11:20	13:58	20:27	13:58	13:58	13:58	13:58	20:27	18:55	17:58	17:10	13:58	13:58	13:58	13:58
Mean	1:02	0:59	0:46	0:53	0:47	0:42	0:39	0:40	0:34	0:29	0:25	0:51	0:49	0:47	0:45
St. Dev.	2:02	2:14	2:17	2:05	2:01	1:58	1:55	2:13	2:05	1:57	1:51	1:58	1:56	1:53	1:51
N	227	227	227	227	227	227	227	227	227	227	227	227	227	227	227

Sources: Patcom, Perioperative Case Data, EDIS, CBEDs, Simulation Results

Notes: Analysis based on all unit-to-unit transfers between January 1, 2012 and June 30, 2013. Transfer origins include both neuroscience and overflow units. (E.g., ICU-to-Lunder 6 transfer figures include both Lunder 7/8-to-Lunder 6 and Overflow Floor-to-Lunder 6 transfers.)

Bed Wait Time Statistics
Comparison of Historical Data, Current State Model, and Intervention Models
ICU-to-Neuroscience Transfers

ICU-to-Lunder 7/8 Transfers

	Historical Data	Current State Simulation	Just-in-Time Bed Assignments	Earlier Discharges: 11 AM Discharge Schedule	Earlier Discharges: 10 AM Discharge Schedule	Earlier Discharges: 9 AM Discharge Schedule	Earlier Discharges: 8 AM Discharge Schedule	Earlier Discharges and Just-in-Time Bed Assignments: 11 AM Disch. Schedule + J.i.T.	Earlier Discharges and Just-in-Time Bed Assignments: 10 AM Disch. Schedule + J.i.T.	Earlier Discharges and Just-in-Time Bed Assignments: 9 AM Disch. Schedule + J.i.T.	Earlier Discharges and Just-in-Time Bed Assignments: 8 AM Disch. Schedule + J.i.T.	Length of Stay Reductions: 1 Day Earlier	Length of Stay Reductions: 2 Days Earlier	Length of Stay Reductions: 3 Days Earlier	Length of Stay Reductions: 4 Days Earlier
Wait Length Frequencies (# of Patients)															
0 Min	959	1,116	978	1,093	1,235	1,504	1,782	1,093	1,235	1,504	1,782	1,290	1,408	1,527	1,638
> 0 Min	1,423	1,266	1,404	1,289	1,147	878	600	1,289	1,147	878	600	1,092	974	855	744
> 30 Min	1,269	1,137	1,265	1,146	981	706	437	1,146	981	706	437	989	879	771	667
> 60 Min	1,145	1,041	1,144	1,016	824	555	290	1,016	824	555	290	899	802	706	602
> 120 Min	905	812	858	684	501	259	118	684	501	259	118	717	630	554	476
> 180 Min	678	613	555	404	242	113	39	404	242	113	39	534	477	416	360
> 240 Min	521	453	298	189	89	37	23	189	89	37	23	380	331	283	250
Wait Time Summary Statistics (hh:mm)															
Min	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00
P5	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00
P25	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00
Median	0:49	0:17	0:49	0:19	0:00	0:00	0:00	0:19	0:00	0:00	0:00	0:00	0:00	0:00	0:00
P75	3:31	3:07	2:51	2:18	1:42	0:51	0:01	2:18	1:42	0:51	0:01	2:38	2:12	1:47	1:03
P95	7:14	7:08	5:07	4:26	3:48	2:57	2:00	4:26	3:48	2:57	2:00	6:39	6:08	6:00	5:37
Max	13:23	21:21	23:21	21:00	19:58	19:11	17:58	21:00	19:58	19:11	17:58	21:21	21:21	21:21	9:51
Mean	2:00	1:48	1:38	1:19	1:00	0:39	0:22	1:19	1:00	0:39	0:22	1:32	1:21	1:10	0:59
St. Dev.	2:31	2:30	2:07	1:55	1:42	1:28	1:15	1:55	1:42	1:28	1:15	2:21	2:14	2:05	1:54
N	2,382	2,382	2,382	2,382	2,382	2,382	2,382	2,382	2,382	2,382	2,382	2,382	2,382	2,382	2,382

ICU-to-Lunder 6 Transfers

	Historical Data	Current State Simulation	Just-in-Time Bed Assignments	Earlier Discharges: 11 AM Discharge Schedule	Earlier Discharges: 10 AM Discharge Schedule	Earlier Discharges: 9 AM Discharge Schedule	Earlier Discharges: 8 AM Discharge Schedule	Earlier Discharges and Just-in-Time Bed Assignments: 11 AM Disch. Schedule + J.i.T.	Earlier Discharges and Just-in-Time Bed Assignments: 10 AM Disch. Schedule + J.i.T.	Earlier Discharges and Just-in-Time Bed Assignments: 9 AM Disch. Schedule + J.i.T.	Earlier Discharges and Just-in-Time Bed Assignments: 8 AM Disch. Schedule + J.i.T.	Length of Stay Reductions: 1 Day Earlier	Length of Stay Reductions: 2 Days Earlier	Length of Stay Reductions: 3 Days Earlier	Length of Stay Reductions: 4 Days Earlier
Wait Length Frequencies (# of Patients)															
0 Min	24	28	31	34	34	34	35	36	38	39	42	29	29	29	30
> 0 Min	21	17	14	11	11	11	10	9	7	6	3	16	16	16	15
> 30 Min	17	12	10	10	10	10	9	6	6	5	2	12	12	12	11
> 60 Min	15	11	10	9	9	8	7	6	6	3	2	10	10	10	10
> 120 Min	13	10	7	7	6	6	6	3	2	1	1	9	9	9	8
> 180 Min	10	8	5	6	6	6	6	1	0	0	0	8	8	8	8
> 240 Min	7	7	4	5	5	4	4	0	0	0	0	7	6	6	6
Wait Time Summary Statistics (hh:mm)															
Min	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00
P5	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00
P25	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00
Median	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00
P75	2:34	0:43	0:12	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:43	0:43	0:36	0:30
P95	5:40	5:31	4:15	5:30	5:23	4:58	4:34	2:36	1:30	1:10	0:24	4:48	4:45	4:45	4:45
Max	6:09	5:53	4:49	5:53	5:53	5:53	5:53	3:06	2:17	2:14	2:14	5:53	5:53	5:53	5:53
Mean	1:20	1:04	0:43	0:49	0:47	0:43	0:39	0:19	0:14	0:09	0:05	1:00	0:59	0:58	0:56
St. Dev.	1:59	1:53	1:26	1:45	1:42	1:35	1:31	0:48	0:35	0:26	0:23	1:48	1:48	1:48	1:47
N	45	45	45	45	45	45	45	45	45	45	45	45	45	45	45

Sources: Patcom, Perioperative Case Data, EDIS, CBEDs, Simulation Results

Notes: Analysis based on all unit-to-unit transfers between January 1, 2012 and June 30, 2013. Transfer origins include both neuroscience and overflow units. (E.g., ICU-to-Lunder 7/8 transfer figures include both Lunder 6-to-Lunder 7/8 and Overflow ICU-to-Lunder 7/8 transfers.)

Bed Wait Time Statistics
Comparison of Historical Data, Current State Model, and Intervention Models
Front Door Clinical Neuroscience Admissions

Front Door Clinical Admissions to Lunder 7/8

				Earlier Discharges				Earlier Discharges and Just-in-Time Bed Assignments				Length of Stay Reductions			
	Historical Data	Current State Simulation	Just-in-Time Bed Assignments	11 AM Discharge Schedule	10 AM Discharge Schedule	9 AM Discharge Schedule	8 AM Discharge Schedule	11 AM Disch. Schedule + J.i.T.	10 AM Disch. Schedule + J.i.T.	9 AM Disch. Schedule + J.i.T.	8 AM Disch. Schedule + J.i.T.	1 Day Earlier	2 Days Earlier	3 Days Earlier	4 Days Earlier
Wait Length Frequencies (# of Patients)															
0 Min	342	469	479	521	563	634	711	534	593	682	766	546	622	696	770
> 0 Min	907	780	770	728	686	615	538	715	656	567	483	703	627	553	479
> 30 Min	848	741	732	692	643	569	497	661	602	518	425	661	587	509	440
> 60 Min	793	695	669	641	597	527	450	607	549	474	361	603	528	454	387
> 120 Min	670	588	546	542	504	430	299	492	435	344	194	505	436	369	312
> 180 Min	523	478	433	444	401	283	170	382	318	183	76	417	368	304	249
> 240 Min	418	385	305	354	267	152	89	261	166	68	22	339	295	241	195
Wait Time Summary Statistics (hh:mm)															
Min	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00
P5	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00
P25	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00
Median	2:21	1:37	1:21	1:12	0:39	0:00	0:00	0:51	0:20	0:00	0:00	0:47	0:02	0:00	0:00
P75	5:09	4:49	3:56	4:26	3:43	2:50	1:55	3:38	3:02	2:12	1:19	4:25	3:43	2:52	2:00
P95	8:08	8:03	6:59	6:57	6:10	5:19	4:23	5:55	5:01	4:05	3:09	7:46	7:30	7:08	6:56
Max	11:33	12:20	23:18	12:20	11:24	11:24	11:24	22:21	21:11	20:21	19:47	12:20	12:20	12:20	12:20
Mean	2:56	2:37	2:15	2:15	1:54	1:28	1:04	1:52	1:32	1:07	0:44	2:18	1:59	1:40	1:24
St. Dev.	2:51	2:52	2:34	2:33	2:16	1:56	1:36	2:15	1:58	1:38	1:19	2:49	2:41	2:31	2:22
N	1,249	1,249	1,249	1,249	1,249	1,249	1,249	1,249	1,249	1,249	1,249	1,249	1,249	1,249	1,249

Clinical Front Door Admissions to Lunder 6

				Earlier Discharges				Earlier Discharges and Just-in-Time Bed Assignments				Length of Stay Reductions			
	Historical Data	Current State Simulation	Just-in-Time Bed Assignments	11 AM Discharge Schedule	10 AM Discharge Schedule	9 AM Discharge Schedule	8 AM Discharge Schedule	11 AM Disch. Schedule + J.i.T.	10 AM Disch. Schedule + J.i.T.	9 AM Disch. Schedule + J.i.T.	8 AM Disch. Schedule + J.i.T.	1 Day Earlier	2 Days Earlier	3 Days Earlier	4 Days Earlier
Wait Length Frequencies (# of Patients)															
0 Min	93	110	121	115	118	122	124	124	126	128	132	113	113	115	116
> 0 Min	55	38	27	33	30	26	24	24	22	20	16	35	35	33	32
> 30 Min	50	34	25	30	27	22	17	21	19	18	15	32	31	29	29
> 60 Min	40	30	22	27	24	20	15	18	15	13	10	30	29	28	28
> 120 Min	29	24	15	20	16	13	12	12	9	7	6	22	21	21	19
> 180 Min	16	14	11	11	9	9	7	7	4	2	2	13	11	10	10
> 240 Min	11	9	7	8	7	6	5	2	1	1	1	9	7	7	7
Wait Time Summary Statistics (hh:mm)															
Min	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00
P5	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00
P25	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00
Median	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00
P75	1:04	0:10	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00	0:00
P95	5:13	4:11	3:55	4:09	3:52	3:28	2:31	2:53	2:09	1:53	1:49	4:11	3:41	3:41	3:41
Max	11:05	18:09	7:32	18:09	18:09	18:09	18:09	6:30	6:26	5:14	4:36	18:09	18:09	18:09	18:09
Mean	0:58	0:49	0:31	0:42	0:37	0:32	0:28	0:23	0:18	0:15	0:12	0:45	0:43	0:42	0:41
St. Dev.	1:52	2:06	1:19	2:01	1:56	1:54	1:51	1:03	0:54	0:45	0:41	2:03	2:00	1:59	1:59
N	148	148	148	148	148	148	148	148	148	148	148	148	148	148	148

Sources: Patcom, Perioperative Case Data, EDIS, CBEDs, Simulation Results

Notes: Analysis based on all clinical front door admissions to Lunder 6, 7, and 8 between January 1, 2012 and June 30, 2013.

Appendix G – Bed Utilization of Neuroscience Units

Bed Utilization of Neuroscience Units

Scenario	Lunder 7/8 Floors: Occupied Bed-Hours (% of Total)	Lunder 7/8 Floors: Unoccupied Bed-Hours (% of Total)	Lunder 7/8 Floors: Change from Baseline Unoccupied	Lunder 6 ICU: Occupied Bed-Hours (% of Total)	Lunder 6 ICU: Unoccupied Bed-Hours (% of Total)	Lunder 6 ICU: Change from Baseline Unoccupied
Historical Data	94.4%	5.6%		89.7%	10.3%	
Current State Simulation	94.2%	5.8%		89.3%	10.7%	
Just-in-Time Bed Assignments	94.0%	6.0%	0.2%	89.2%	10.8%	0.1%
Earlier Discharges						
11 AM Discharge Schedule	93.6%	6.4%	0.6%	88.9%	11.1%	0.4%
10 AM Discharge Schedule	93.1%	6.9%	1.2%	88.7%	11.3%	0.6%
9 AM Discharge Schedule	92.3%	7.7%	1.9%	88.4%	11.6%	0.9%
8 AM Discharge Schedule	91.5%	8.5%	2.7%	88.1%	11.9%	1.2%
Earlier Discharges and Just-in-Time Bed Assignments						
11 AM Discharge Schedule & Just-in-Time Bed Assignments	93.5%	6.5%	0.8%	88.8%	11.2%	0.5%
10 AM Discharge Schedule & Just-in-Time Bed Assignments	93.0%	7.0%	1.3%	88.6%	11.4%	0.7%
9 AM Discharge Schedule & Just-in-Time Bed Assignments	92.3%	7.7%	1.9%	88.3%	11.7%	1.0%
8 AM Discharge Schedule & Just-in-Time Bed Assignments	91.5%	8.5%	2.7%	88.0%	12.0%	1.3%
Length of Stay Reductions						
1 Day Earlier	93.2%	6.8%	1.0%	89.1%	10.9%	0.2%
2 Days Earlier	92.3%	7.7%	1.9%	89.0%	11.0%	0.3%
3 Days Earlier	91.2%	8.8%	3.1%	88.9%	11.1%	0.4%
4 Days Earlier	90.0%	10.0%	4.2%	88.8%	11.2%	0.5%

Sources: Patcom, Perioperative Case Data, EDIS, CBEDs, Simulation Results

Notes: Bed utilizations are calculated between January 1, 2012 and June 30, 2013. The total bed capacity during this time is 35,008 bed-days (= 547 days x 64 beds) for Lunder 7/8, and 12,034 bed-days (= 547 days x 22 beds) for Lunder 6. A bed is considered utilized when (1) a patient currently occupies the bed, (2) the bed is being cleaned, or (3) a patients has left the bed to have surgery and will return to the bed post-surgery.

Appendix H – Delays Unrelated to Bed Availability (DUBA)

Cumulative Delay Unrelated to Bed Availability (DUBA)

	Lunder 7/8 Floors		Lunder 6 ICU	
Scenario	**DUBA (Hours)**	**DUBA (Days)**	**DUBA (Hours)**	**DUBA (Days)**
Historical Data	6,494	270.6	1,147	47.8
Current State Simulation	5,313	221.4	1,088	45.3
Just-in-Time Bed Assignments	348	14.5	189	7.9
Earlier Discharges				
11 AM Discharge Schedule	5,466	227.8	1,075	44.8
10 AM Discharge Schedule	5,621	234.2	1,074	44.8
9 AM Discharge Schedule	5,576	232.3	1,096	45.7
8 AM Discharge Schedule	5,397	224.9	1,109	46.2
Earlier Discharges and Just-in-Time Bed Assignments				
11 AM Discharge Schedule & Just-in-Time Bed Assignments	443	18.5	206	8.6
10 AM Discharge Schedule & Just-in-Time Bed Assignments	425	17.7	199	8.3
9 AM Discharge Schedule & Just-in-Time Bed Assignments	403	16.8	196	8.2
8 AM Discharge Schedule & Just-in-Time Bed Assignments	387	16.1	192	8.0
Length of Stay Reductions				
1 Day Earlier	6,425	267.7	1,142	47.6
2 Days Earlier	7,016	292.3	1,084	45.2
3 Days Earlier	7,140	297.5	1,098	45.8
4 Days Earlier	7,169	298.7	1,085	45.2

Sources: Patcom, Perioperative Case Data, EDIS, CBEDs, Simulation Results

Notes: The cumulative delay unrelated to bed availability (DUBA) is calculated between January 1, 2012 and June 30, 2013. DUBA is defined as the total bed wait time incurred by patients during the period of study while clean beds are available in their destination units. This delay can be eliminated through instantaneous just-in-time bed assignments for all patients. No additional bed capacity is required to eliminate this delay. The remaining DUBA in the just-in-time bed assignment scenario above reflects bed assignment delays for ED patients (i.e., bed assignments for ED patients are not instantaneous).