Improving Surgical Patient Flow through Simulation of Scheduling Heuristics

by

Ashleigh Royalty Range

B.S. Industrial and Systems Engineering, Georgia Institute of Technology, 2007

Submitted to the MIT Sloan School of Management and the Engineering Systems Division in Partial Fulfillment of the Requirements for the Degrees of

Master of Business Administration
and
Master of Science in Engineering Systems

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

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Abstract

Massachusetts General Hospital (MGH) is currently the nation's top ranked hospital and is the largest in New England. With over 900 hospital beds and approximately 38,000 operations performed each year, MGH's operating rooms (ORs) run at 90% utilization and their hospital beds at 99% operational occupancy. MGH is faced with capacity constraints throughout the perioperative (pre-, intra-, and post-operative) process and desires to improve throughput and decrease patient waiting time without adding expensive additional resources.

This project focuses on matching the intraday scheduling of elective surgeries with the discharge rate and pattern of patients from the hospital floor by investigating ways surgeons could potentially schedule their cases within a given OR block. To do this, various scheduling rules are modeled to measure the impact of shifting patient flow in each step of the perioperative process.

Currently the hospital floor proves to be the biggest bottleneck in the system. Delays in discharging patients result in Same Day Admits (patients that will be admitted to the hospital post-surgery) waiting for hospital beds in the Post Anesthesia Care Unit (PACU). These patients wait more than sixty minutes on average after being medically cleared to depart the PACU.

A simulation model is built to evaluate the downstream effects of each scheduling rule and discharge process change. The model takes into account physical and staff resource limitations at each of the upstream and downstream steps in the perioperative process. By scheduling Same Day Admits last in each OR block, patient wait time in the PACU can be reduced up to 49%.

By implementing the recommended changes the system will realize lower wait times for patients, less stress on the admitting and nursing staff, and a better overall use of the limited physical resources at MGH.

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1 Introduction

Recent healthcare legislation is forcing hospitals to restructure their current operations (Andrews, 2012). Because of this and other external factors, the costs for providing care are rising (Marcario, Vitez, Dunn, & McDonald, 1995). One of the most important areas of a hospital, financially, is the perioperative department, because it handles all stages of a surgical patient's operation. This area is typically the largest revenue and cost driver for a hospital (Health Care Financial Management Association, 2005). However, it is often difficult to make the necessary adjustments and changes due to the conflicting priorities of the many stakeholders that exist in a hospital system (Glauberman & Mintzberg, 2001). As the population ages, demand will be increasing, therefore changes to operational efficiency must be made (Etzioni, Liu, Maggard, & Ko, 2003).

1.1 Massachusetts General Hospital

The Massachusetts General Hospital (MGH) is the third oldest hospital in the United States and in July 2012 was named America's best hospital by U.S. News & World Report (Massachusetts General Hospital, 2012). The 907-bed medical center admits 47,000 inpatients, handles close to 1.4 million outpatient visits, and records 88,000 emergency room visits annually. MGH is the original and largest teaching hospital of Harvard Medical School. With an annual research budget of nearly $764 million, Mass General conducts the largest hospital-based research program in the United States. With the recent opening of the Lunder building, MGH increased its capacity from 52 to 70 operating rooms to handle the 38,000 operations performed each year (Massachusetts General Hospital, 2012).

1.2 MIT – MGH Collaboration

Over the past six years, MGH and Massachusetts Institute of Technology (MIT) have formed a partnership to address operational effectiveness within the hospital. Faculty and post-doctorate students within the Operations Management group along with students in the Leaders for Global Operations

(LGO) program have teamed up with MGH leadership to study and implement changes to benefit the hospital.

Two previous projects have focused on improving the scheduling system of surgeries at MGH. The first is the operating room (OR) block optimization project (Price, 2011). This project aimed to reduce the midnight census (number of patients in the hospital overnight) throughout the days of the week by optimizing surgeon-assigned block dates. Each surgeon is given access to a particular operating room on certain days of the week and this is called an OR block. By changing the dates when surgeons have access to operating rooms the average peak patient occupancy in the middle of the week was lowered.

The second project modified the way non-elective patients were added to the OR schedule. Non-elective cases typically originate in an unplanned manner from patients either currently in the hospital or from the Emergency Department. These patients are placed on a waitlist and scheduled for surgery within minutes, hours, or up to 24 hours depending on the severity of their condition. It is very important that these patients get off the waitlist, onto the OR schedule, and into surgery as soon as possible. This project reduced the amount of time it takes for a non-elective patient to be scheduled into the OR by dedicating operating rooms and *open blocks* (i.e., blocks accessible to groups of surgeons) to handle these types of cases.

The project discussed in this thesis extends the block optimization project; while the block optimization project aimed to lower the weekday peak in patient occupancy, this project aims to address the midday peak occupancy of patients. As some patients enter the hospital system and others depart each day there is a period of time when the number of patients requiring beds is greater than the number of beds available. This project evaluates various scheduling heuristics via a simulation model to see if improvements can be made in the intraday patient census. The model takes knowledge gained through the waitlist project and uses it as additional constraints when making improvements to the system.

1.3 MGH OR Scheduling System

The Perioperative Services department at MGH oversees the flow of surgical patients during their day of surgery. Areas that the perioperative department is responsible for include: Center for Perioperative Care (CPC), Lunder and Legacy Operating Rooms (OR), the perioperative bays in Lunder, and Post Anesthesia Care Units (PACU). Additionally there are several hospital floors dedicated to serving surgical patients that are involved in a surgical patient's care. A listing of locations for each of these areas and their capacities can be found in Appendix 6.1.

Figure 1 represents a high level description of how a patient flows through MGH's perioperative process. An elective[1] patient will schedule their surgery through their surgeon's office. On the day of surgery a patient has their operation completed and then recovers in either the Post Anesthesia Care Unit (PACU) or the Intensive Care Unit (ICU) depending on the level of care needed. If it is an outpatient, she would be discharged from the PACU and go home. If it is an inpatient she would proceed from the PACU to the hospital floor where eventually she would be discharged. Appendix 6.2 contains a more detailed view of each patient type's flow through the perioperative process.

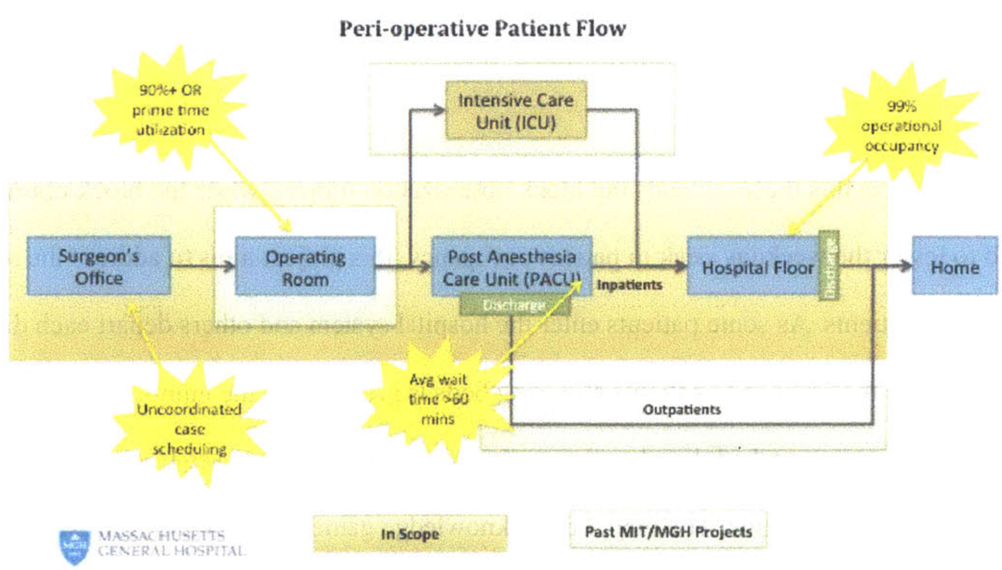


Figure 1: High-level surgical patient flow

[1] An electively scheduled patient is one who plans the surgery in advance with a surgeon. This is in contrast to the non-elective or waitlist cases that are schedule the day-of surgery in a more emergent situation.

1.3.1 OR Schedule

To understand the OR scheduling system at MGH one has to focus on four main domains of activities. These are OR scheduling, PACU departures, floor discharges, and bed assignments as seen in Figure 2.

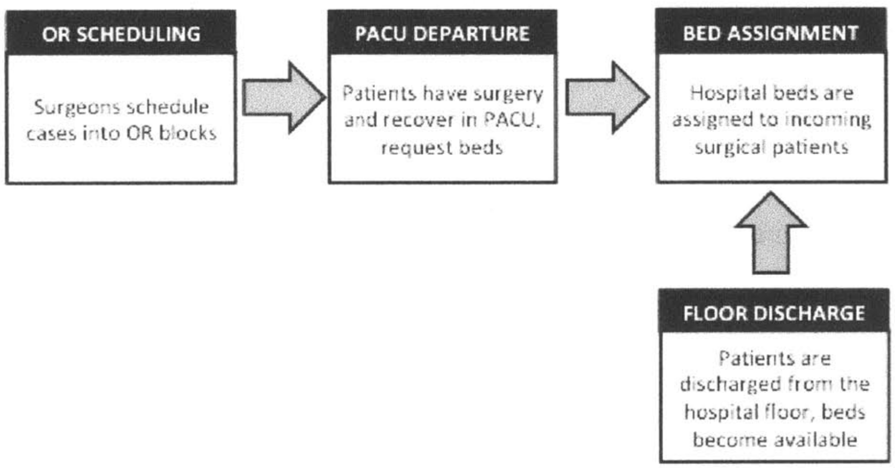


Figure 2: OR Scheduling System

The patient's surgery is scheduled through their surgeon who has been assigned a specific operating room block. As previously discussed, the OR block allows the surgeon to book the cases she would like on a fixed given day of the week in a certain fixed operating room during prime-time which is generally 8:00AM-5:00PM weekdays. (Blocks are typically first assigned to surgical services, and then each of the chiefs of the surgical services assign these blocks to individual surgeons in the respective departments.) Currently, the surgeon can schedule patients however they deem best for their practice. No one position looks across the system to see how each individual surgeon's schedule affects the flow overall.

1.3.2 Perioperative Care

Based on the timing of when patients' operations are scheduled, patients arrive at the hospital and are processed through a series of steps concluding with recovery in the PACU. The PACU has dual functionality for its surgical patients— 1) preparing patients before surgery, and 2) initially caring for patients post-surgery. Because of these locations' dual functionality, these areas are referred to as the perioperative bays. There are other patients also using these pre- and post-operation areas including

Endoscopy, Radiology, and Electrotherapy (ECT). These non-surgical patients provide additional constraints on the capacity of each perioperative location. The OR Administrator manages day-of changes to the schedule. Nursing staff from the perioperative department manages the flow of patients through the perioperative bays.

1.3.3 Floor Discharges

As mentioned above, after initially recovering in the PACU, many patients spend several days on a hospital floor to be monitored and continue their recovery. Once patients on the hospital floors are medically ready to leave, they are discharged from the hospital to either go home or to a rehabilitation facility. Doctors managing the patient's care decide what day a patient is ready to be discharged. Nurses on each hospital floor manage the process of discharging the patient. A patient that is discharged frees up a bed on the respective floor, which after an appropriate cleaning becomes available for another patient.

1.3.4 Bed Assignments

The Admitting Department at MGH manages the flow of patients through the hospital system including the assignment of hospital floor beds to surgical and other patients. They work as an intermediary between the OR staff and the hospital floor staff to match patients needing beds to available beds. In addition to finding beds for surgical patients, admitting also must manage requests from the emergency department, the catheterization laboratory, the medicine department, the ICU, front door admissions, and other departments. Currently, the timing of a PACU patient needing a bed is not in sync with the timing of discharges from the hospital. MGH has extremely high hospital floor utilization (above 99%). When there is not a hospital floor bed available for a PACU patient, patients must wait in the PACU. If the PACU becomes full, then the patient must begin the recovery process in the operating room (a highly expensive resource), until the downstream steps are decongested. The PACU has become a system buffer between the OR and the Floors.

Each morning admitting staff takes the daily surgical schedule to the hospital floors to make bed assignments. Nursing management from the hospital floor comes to the meeting with a list of all the likely discharges for the day. Together, they go through the list of surgical patients needing beds starting with the earliest surgeries first and make assignments. Bed assignments are made with rooms of patients most likely to be discharged that day. Often admitting leaves with patients that are still unassigned because there are more surgical patients than discharges. These bed assignments are used unless an admitting staff member notices throughout the day that there is a floor bed available and a patient waiting in the PACU that meets the requirements for that available bed.

1.3.5 Communication Requirements

After a patient is discharged from a hospital floor bed, many steps must occur before a surgical patient can depart the PACU for that bed. There are often communication delays between nursing on the hospital floor, nursing in the PACU and admitting staff personnel that prevent these steps from occurring in a timely manner.

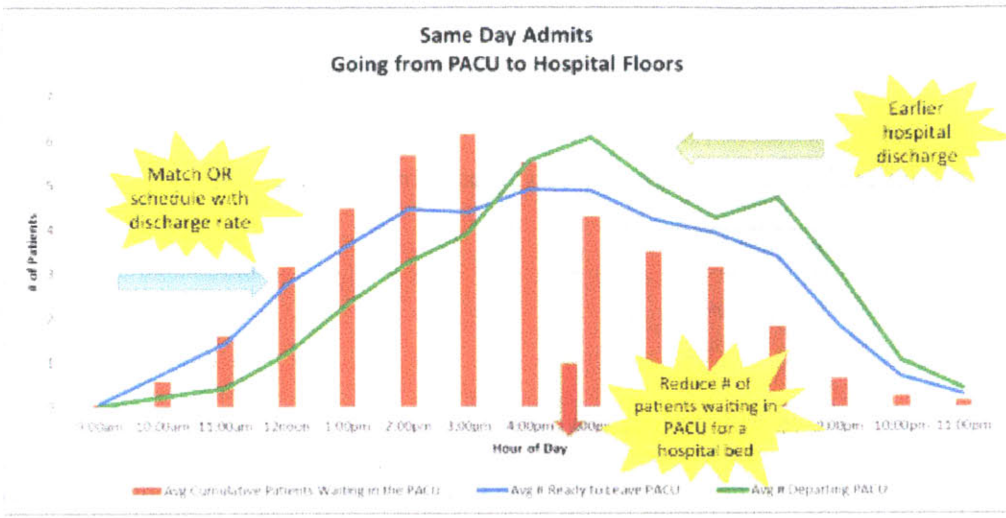
First, the bed must be cleaned, requiring cleaning staff availability. Once the cleaning staff has completed sanitizing the room, it is marked as cleaned in the system. It then needs to be communicated to the PACU that the bed is ready for the patient assigned to it. Even if a bed is assigned, a nurse might not be assigned to that patient yet. Once a nurse is assigned, the nurse needs to be ready to accept the patient. The assigned nurse could be tending to or in the middle of a discharge or admission of another patient, or even on a break. Once the assigned nurse is available, the PACU nurse must be able to connect with them via phone to do the verbal handoff between floors. Transport staff is then requested to move the patient but again, these staff members are not always available right away and the PACU nursing staff must wait until the transport staff returns from other trips. There is also a chance that the PACU nursing staff (knowing all the delays in the bed assignment and staff communication) may denote the patient is medically ready to leave the PACU in the system when in reality there is still addition steps that need to occur before the patient is truly ready to depart the PACU. This also causes delays until that patient is medically ready to leave.

If any one of these steps has complications or is not communicated well, the surgical patient could wait additional time in the PACU, even if they are medically ready to leave.

1.4 Project Overview

Next we would like to provide a high level description of the work in this thesis. The perioperative system is critically important both to MGH and to its patients. The operating rooms are the biggest source of revenue for the hospital. The revenue generated goes to support many of the other hospital services. For its patients, MGH is the leading hospital in the U.S. and employs some of the world's leading surgeons.

Figure 3 shows the average number of patients ready to leave the PACU in each hour of the day (in blue) and the average number of patients that actually leave the PACU each hour (in green). The cumulative difference between these two numbers is the number of patients waiting in the PACU for a floor bed by hour (in red). (Data includes Same Day Admit patients, January 2012 through June 2012, non-holiday, weekdays.) Because these two rates are not in sync, patients must wait in the PACU longer than medically necessary. If the PACU becomes full, patients may be forced to begin recovery in the operating rooms. If this happens, the quality of care for the patient is decreased, and the cost to care for that patient rises dramatically.



Patient discharges from the hospital floors are not in sync with admits from the PACU

Figure 3: Project objectives

This project explores the effectiveness of the following levers: 1) changing the order of scheduled patients in a given OR on a given day, 2) changing the timing of discharging patients from the hospital floor, and 3) the method with which bed assignments are made. The first two levers need to be in sync- specifically the rate of same day admit patients that come from home on the day of surgery and need a bed on a surgical floor after the surgery and the patients in the hospital being discharged on the respective day.

In this thesis we investigated several ways of getting these two rates better in sync on a daily basis with the goal that when a patient is ready to leave the PACU there is an appropriate hospital bed available to which they can be transferred with no further delay.

1.4.1 Objectives

The objectives of this project were as follows:

- Understand the current state processes around the OR scheduling system and the associated system limitations (both physical resources and staff resources)
- Model the current perioperative system for all surgical patients to evaluate delays and location-specific occupancy levels

- Estimate the effects of various scheduling, discharge, and bed assignment heuristics on patient PACU wait time
- Recommend solutions for improved patient flow through matching admission and discharge rates from the PACU to the hospital floors

1.4.2 Approach

In depth interviews were conducted with perioperative leadership and key stakeholders that gave insight into current issues in the system. On-site shadowing of line workers provided a clear picture into how the systems operate. With the contextual understanding in mind, data was analyzed to assess the current state and see how best to improve the current processes. After gathering data, a simulation model was built to study and explore the performance of the current scheduling system and to analyze the effects of various scheduling heuristics. The model takes into account physical and staff resource limitations at each of the upstream and downstream steps in the perioperative process. The model output was analyzed to see where the largest gains are and refined to make it more realistic of the actual system.

1.4.3 Results

Based on the data analysis, we identified that there exists an average delay of a 60 minutes between when a Same Day Admit[2] patient is ready to depart until she actually departs the PACU for a hospital bed. 22% of these patients do not have a bed available to them when they are ready to leave. These patients wait an average of 176 minutes to depart the PACU. Of these 176 minutes, 115 minutes are associated with waiting for a hospital bed to become available.

The simulation model revealed improvement opportunities and established rational for several recommended changes:

[2] There were 5,298 Same Day Admit patients between January 2012 and June 2012 during prime-time, non-holiday, weekday surgeries.

1. The first is to assign open beds based on the expected end time instead of based on the operation start time as it is now scheduled. If MGH was able to assign beds to patients dynamically throughout the day on a first come first serve basis there could be a reduction of up to 41% in patient wait time for a hospital bed.
2. Another opportunity for improvement is to systematically schedule patients that will require a bed after surgery (and do not currently have one from before surgery) later in the day. This allows the maximum number of beds to become available before the patient requires one. If all patients that fall into this category were scheduled last, the average number of patients waiting in the PACU after being medically ready to leave would be reduced by 49% compared to the baseline wait time for a hospital bed.
3. Furthermore, the analysis indicated that improving communication between the PACU and hospital floor nursing staff could decrease the baseline total patient wait time in the PACU by 58%.
4. A final recommendation is to discharge patients on the floor more strategically. For example, if all patients were discharged 60 minutes earlier, there would be a 42% reduction in patient wait time for a hospital bed.

1.5 Thesis Outline

This thesis will begin by outlining the key issues found in the OR scheduling process along with quantifying the magnitude of these issues. Next, it will identify several types of potential levers that could be used to improve the system. These potential levers are then integrated into a simulation model and the results are detailed. Finally, the thesis will close with recommendations and practical ways to implement these ideas.

2 Current State Analysis

2.1 Introduction

The first step in improving a system is identifying key areas for potential improvement and developing an understanding of the root causes of those issues. The goal of this analysis is to understand to what extent and why patients wait in the PACU after they are medically ready to leave. The process of moving a patient from the PACU to a hospital floor is a complex one that requires many staff members from different departments, system entries, and communication handoffs.

2.2 Methods

To understand the system, over 30 interviews were conducted with surgeons, admitting staff, OR administration, PACU nursing staff, hospital floor nursing staff, and nursing administration. Several weeks were spent shadowing staff in the OR, PACU, and hospital floors. Bed meetings between admitting staff and nursing floor leadership on White 6, Ellison 6, and Lunder 7 & 8 floors were observed. The hospital-wide capacity, surgical nurse staffing, and the staff administrator daily meetings were regularly attended. Finally, data from both the PRISM perioperative database as well as the admitting database was analyzed. Note that all tables and charts in this chapter are based on PRISM OR data May 2011 through Jan 2012 for electively scheduled patients.

2.3 Key Findings

2.3.1 Scheduling OR Cases

As previously discussed, the OR block schedule allows surgeons to book their cases how they would like on a given day in a certain operating room during prime-time which is generally 8:00AM-5:00PM weekdays. The distribution of the quantity of cases per OR block are found below in Figure 4 and Table 1. The analysis found that 75% of OR blocks contain more than one case.

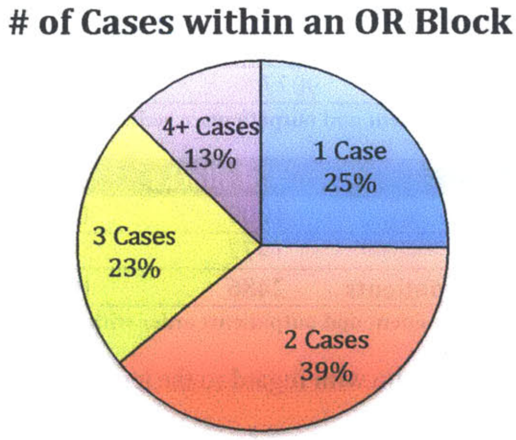


Figure 4: Chart of number of cases within a block

# of Electively Scheduled Cases per OR Block	# of Cases	# of Blocks	% of Blocks
1	2,286	2,286	25%
2	7,056	3,528	39%
3	6,354	2,118	23%
4	3,008	752	8%
5	1,430	286	3%
6	450	75	1%
7	147	21	0%
8	72	9	0%
9	18	2	0%
Total	20,821	9,077	100%

Table 1: Distribution of scheduled cases per block

The following analysis looks at the makeup of OR blocks with regards to patient type. Inpatients are defined as patients staying in the hospital after their operation. Outpatients are defined as patients returning home after their operation. Each OR block (a single operating room during prime time) was analyzed to see what type of patients were operated on. In 27% of the OR blocks, at least one inpatient and at least one outpatient were found within the same OR block. In these mixed patient type blocks, 59% of the blocks scheduled an outpatient as their first case and the other 41% scheduled an inpatient as the first case. These results are found in Table 2 and Table 3.

	# of Blocks	% of Blocks
Only Inpatients	4181	46%
Only Outpatients	2410	27%
Both in/outpatients	**2486**	27%
Total Blocks	9077	100%

Table 2: Inpatient and outpatients scheduled in blocks

	# of Blocks	% of Blocks
Inpatient first	1009	41%
Outpatient first	1477	59%
Total **Both in/outpatients**	**2486**	100%

Table 3: Inpatient and outpatients order within blocks

OR blocks were again analyzed but this time with regard to the length of the cases. Cases were labeled as less than two hours, in between two and four hours and greater than four hours. Each OR block was studied to see which length cases it contained. The analysis found that in 43% of the OR blocks, there is some combination of less than two hour cases, between two and four hour cases, and longer than four hour cases. In these mixed case length blocks, 41% schedule the shorter than two hour cases first, 38% schedule a between two and four hours case first, and 21% schedule a longer than four hours case first. Results are found in Table 4 and Table 5.

	# of Blocks	% of Blocks
Mixed case-length blocks	**3885**	43%
Only <2 hour cases	1263	14%
Only >4 hour cases	1923	21%
Only 2-4 hour cases	2006	22%
Total Blocks	9077	100%

Table 4: Length of cases scheduled in blocks

	# of Blocks	% of Blocks
<2 first	1593	41%
>4 first	834	21%
2-4 first	1458	38%
Total Mixed case-length blocks	**3885**	100%

Table 5: Length of cases order within blocks

The final analysis performed on this set of data took a count of unique surgeons operating in the same OR block on a given day. Table 6 shows the results of this analysis. 28% of OR blocks contain two or more surgeons operating.

# of Surgeons	# of Blocks	% of Blocks
1	6514	72%
2+	2563	28%
Grand Total	9077	100%

Table 6: Number of surgeons within blocks

From the interviews with staff members we could identify a diversity of scheduling strategies different surgeons use:

- Outpatients first to allow patients to go home earlier
- Shorter cases before longer cases to ensure the second case can be started during prime time
- Longer cases before shorter cases as the surgeon feels they are sharpest in the morning
- Complex cases with extended prep time first so that the prep time can happen outside the OR block time (typically starting at 8:00AM)

In fact, the most common sequencing method was "*whatever is available*". It is quite clear that there is no standard process for scheduling the surgical cases into blocks. Moreover, all of the above strategies are not driven at all by considerations of bed availability.

2.3.2 Hospital Floor Capacity Issues

Hospital beds are currently the biggest bottleneck in the MGH system. This assertion is supported anecdotally by the fact that the hospital floor is at over 100% capacity during the middle of the day. This causes patients to stay in the PACU until a bed becomes available even if they are medically ready to leave. The PACU faces delays driven by hospital bed capacity issues every day. This makes it difficult for hospital staff and administration to make strategic decisions about patient placement.

Delays in discharging patients from the hospital in a timely manner significantly affect these capacity issues. The reasons for the delays in discharging patients include downstream capacity issues at rehabilitation centers, extensive number of parties and paperwork involved in the discharge process, patient driven delays such as ride home availability, and technically empty beds that cannot be used due to gender and infectious disease bed requirements.

2.3.3 Current State Wait Time Analysis

One of the key metrics analyzed in the current state was wait time for PACU patients requesting hospital floor beds post-surgery. In the absence of a better indicator, we considered the time a "floor bed" is requested as the moment when it was decided the patient is ready to leave the PACU. Respectively, wait time is defined as the number of minutes after a patient becomes medically ready to leave until the actual time when they left the PACU. A system reduction in this metric would reduce the total number of patients in the PACU and allow for higher throughput with the same level of resources. Two aspects affect the wait time of a patient—what time they are medically ready to leave and when a bed becomes available on the hospital floor. Current state wait time analysis was conducted on PRISM OR Data January 2012 through June 2012 for electively scheduled Same Day Admit patients during non-holiday, weekday operations between the hours of 8:00AM and 5:00PM.

Figure 5 gives two examples of how patient wait times are calculated in the current state analysis and in the simulation model described in Section 0. The first patient in this example arrives to the PACU at 3:00 PM, is medically ready to leave at 4:30 PM but there is not a bed ready for them at that time. A bed is finished being cleaned at 5:00 PM and in the analysis (and simulation model described further in this document) they would depart directly to the hospital floor at 5:00 PM. Therefore this patient's wait time is 30 minutes. In the second example the patient again arrives to the PACU at 3:00 PM but this one is medically ready to leave at 6:00 PM. A bed is finished being cleaned at 5:00 PM again, an hour before the patient needs it. Since there is a bed available for the patient at 6:00PM they are able to depart the PACU immediately and have zero wait time.

Patient Wait Time Calculation - Example

Patient #	Arrives to PACU	Medically Ready to Leave	BedNotification Arrives	Patient Departs	Patient Wait Time
940382	3:00PM	4:30PM	5:00PM	5:00PM	30 minutes
931739	3:00PM	6:00PM	5:00PM	6:00PM	0 minutes

Figure 5: Patient wait time calculation example

The example above demonstrates how wait time is calculated. This calculation is shorter than the length of time a patient actually spends waiting in the PACU after they are medically ready to leave. Recall that in addition to a bed being available for the patient, there is additional processing that needs to occur prior to their departure from the PACU (see Section 1.3.5 Communication Requirements for more details).

Table 7 includes total wait time statistics (time between a patient being medically ready to depart the PACU until actual departure) for Same Day Admits. We focused on Same Day Admits because they are patients that will require a new hospital bed post-surgery. Outpatients return home after their surgery and do not need a hospital floor bed. Inpatients return to the same bed from which they came so they do not need a new hospital floor bed. See Appendix 6.4 for definitions of statistics used to measure wait times in this thesis.

Minutes between Ready to Depart and Departed PACU for Same Day Admits	
Mean	60
Median	15
Minimum	-
Maximum	679
25% Quantile	1
50% Quantile	15
75% Quantile	82
85% Quantile	142
90% Quantile	190
95% Quantile	263
Standard Deviation	94
% Not Waiting	22%
% Waiting	78%
Average wait time for patients with wait time >0	176

Table 7: Total actual wait time (PACU Ready to PACU Depart) statistics

Focusing on Same Day Admits, we found that 22% of these patients do not have a hospital bed available to them when they are medically ready to leave the PACU. The average delay (wait time) of those delayed is 176 minutes (see Figure 6). Interestingly, out of these 176 minutes, 115 minutes on average, are due to lack of available bed and other 61 minutes are waiting for the bed to be cleaned and the patient being transported.

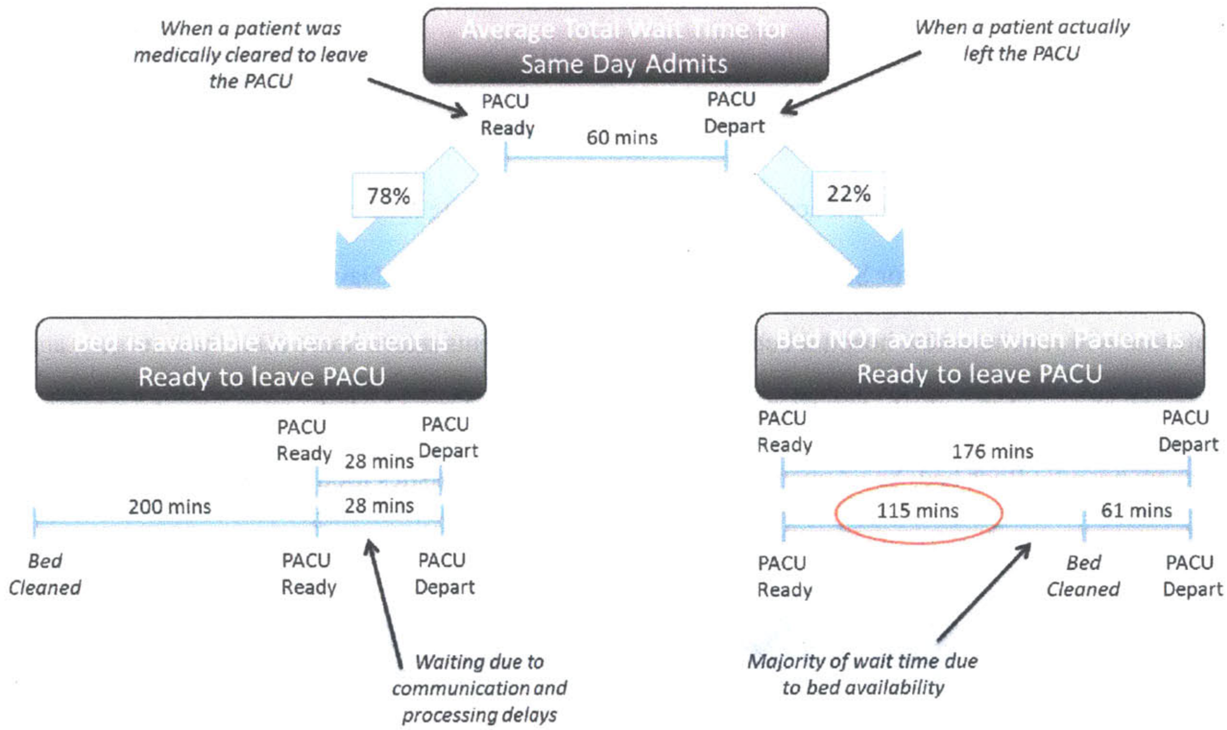


Figure 6: Wait time by bed availability

One assumption to note is that in this analysis and the simulation model (described in Section 0), patients go to beds on a first come first serve basis (assuming the patients meet the requirements for the bed discussed in Section 4.2.3.4). In reality, however, patients are assigned beds at the beginning of the day according to their operation start time not their expected end time. Therefore there may be some inefficiency in the system due to patients waiting for a bed when in reality there is a bed available for them but no one is aware (see Section 1.3.4 Bed Assignment for more details).

The current state baseline allows patients to go to the beds they went to historically and calculates wait times as the difference between when a patient was medically ready to leave and when their bed was cleaned. The following sections will focus on reducing this population's wait time for a bed. Results for the patient wait time for a bed are found below:

Wait Time Analysis	Baseline
Mean	25
Maximum	661
85% Quantile	47
90% Quantile	94
95% Quantile	171
Standard Deviation	67
% Not Waiting	78%
% Waiting	22%
Average wait time for patients with wait time >0	115

Table 8: Baseline actual wait time for a bed to be cleaned (PACU Ready to Bed Cleaned)

Figure 7 shows how the wait time changes depending on when the patient becomes medically ready to leave the PACU for patients whose bed is not cleaned by the time they are ready to depart. The red line represents the number of Same Day Admit patients ready each hour. The green bars represent the average time a patient waits for a hospital bed to be cleaned. The blue bars represents the average time between when the patient's bed is cleaned and when they are able to depart the PACU. Patients wait in the PACU for a hospital bed longer on average the earlier in the day they arrive. This makes initiative sense as well—throughout the day patients are discharged, opening up hospital floor beds. The time between when a bed is cleaned and a patient leaves the PACU is steadier throughout the day. The communication delays associated with bed assignment and patient movement decreases throughout the day but not nearly as dramatically as the time waiting for a bed to be cleaned does.

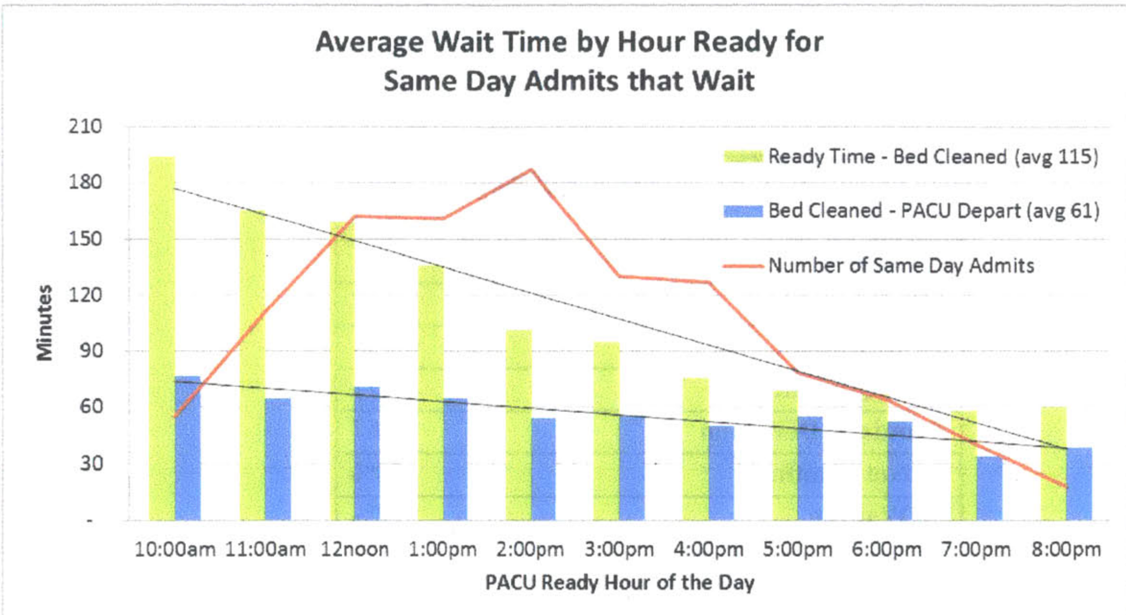


Figure 7: Same Day Admit wait time by hour ready

3 Potential Levers and Solutions

3.1 Introduction

In an effort to evaluate the impact of potential scheduling, discharge, and bed assignment heuristics on patient's wait times, changes were made to the order of operations in a given room on a given day. Scenario heuristics were chosen over more precise mathematical models in an effort to ease implementation of a potential solution. There are many benefits of using heuristics as outlined in Appendix 6.4 (Gigerenzer, 2008). The following sections describe each potential policy and process change.

3.2 Scheduling Heuristics

The first potential lever is scheduling the surgical cases in a given operating room following specific heuristics. In-scope cases include surgical cases performed January 2012 through June 2012 on weekdays, non-holidays, and during prime-time (8:00AM-5:00PM). Non-elective, waitlist surgical cases and operating rooms with multiple surgeons were included in the reordered cases.

3.2.1 Shortest Cases First

The first heuristic schedules cases based on their respective predicted minutes, from shortest to longest. Note that the actual case length will be different than the scheduled time and may have been in a different order if one knew how long the surgeries would actually take. However, for this analysis we are testing solutions that could be used in the future by an OR Administrator that would only know the scheduled minutes when rearranging the next day's schedule. The following table is an example of how an operating room would be rescheduled based on this heuristic.

Patient Category	Date	Operating Room Number	Actual Order	*Shortest Cases First Order*	*Scheduled Case Length*	Actual Case Length
IN	1/3/2012	1	3	**1**	**56**	54
AS	1/3/2012	1	2	**2**	**106**	138
RR	1/3/2012	1	1	**3**	**119**	119

Table 9: Shortest cases first reordering example

3.2.2 Longest Cases First

The next scheduling heuristic has similar methodology as the previous one, Shortest Cases First, but the order is now the longest cases go first. Again, the case order is based on scheduled length, not on the actual length to make the heuristic feasible. The following table is an example of how an operating room would be rescheduled based on this heuristic.

Patient Category	Date	Operating Room Number	Actual Order	*Longest Cases First Order*	*Scheduled Case Length*	Actual Case Length
RR	1/3/2012	1	3	**1**	**119**	119
AS	1/3/2012	1	2	**2**	**106**	138
IN	1/3/2012	1	1	**3**	**56**	54

Table 10: Longest cases first reordering example

3.2.3 Outpatients First

In this heuristic, patients categorized as Ambulatory Surgery (AS) (Outpatients) are scheduled first in the day before all other patient categories. The following table is an example of how an operating room would be rescheduled based on this heuristic.

Patient Category	Date	Operating Room Number	Actual Order	*Outpatients First Order*
AS	1/3/2012	1	2	**1**
RR	1/3/2012	1	1	**2**
IN	1/3/2012	1	3	**3**

Table 11: Outpatients first reordering example

3.2.4 Same Day Admits Last

Patients categorized as Same Day Admit (SD) are scheduled last after all other patient categories. The following table is an example of how an operating room would be rescheduled based on this heuristic.

Patient Category	Date	Operating Room Number	Actual Order	*SDA Last Order*
AS	1/3/2012	10	3	**1**
SD	1/3/2012	10	1	**2**
SD	1/3/2012	10	2	**3**

Table 12: Same Day Admits last reordering example

3.2.5 Same Day Admit, Observation, and RPPR Last

Observation and RPPR patients also require hospital floor beds after being medically ready to depart the PACU. This heuristic includes these patient categories with the Same Day Admits scheduled at the end of the day. The following table is an example of how an operating room would be rescheduled based on this heuristic.

Patient Category	Date	Operating Room Number	Actual Order	*SDA/OBS/RR Last Order*
AS	1/3/2012	1	2	**1**
IN	1/3/2012	1	3	**2**
RR	1/3/2012	1	1	**3**

Table 13: Same Day Admits, Observation, and RPPR reordering example

3.2.6 Random

The final general heuristic we are evaluating is random scheduling to test whether the way MGH is currently scheduling patients is an improvement from a policy in which patients are simply being randomly scheduled. The following table is an example of how an operating room would be rescheduled based on this heuristic.

Patient Category	Date	Operating Room Number	Actual Order	*Rand() Generated Number*	*Random Order*
RR	1/3/2012	1	1	**1**	**1**
IN	1/3/2012	1	3	**2**	**2**
AS	1/3/2012	1	2	**3**	**3**

Table 14: Random reordering example

3.3 Scheduling Constraints

There are two main constraints that potentially limit the order of surgical cases within a given block. Those are that waitlist (non-elective) cases and cases in rooms with multiple surgeons operating throughout the day cannot be moved. Each of these constraints will be applied to the best-case scenario individually and then combined.

3.3.1 Waitlist Constraint

Waitlist cases are patients that are scheduled the day-of surgery in an unplanned manner. These cases typically come from the Emergency Department. There are three category types for these cases: Urgent, Emergent, and Non-Urgent. They each require a different maximum time for the OR Administrator to get them on to the schedule and into surgery. Because we do not know what waitlist cases will be on the schedule for the following day, it is not reasonable to assume that we can shift these cases in the schedule on the day before. See Appendix 6.6.1 for details on the logic applied to incorporate this constraint into the analysis.

3.3.2 Multiple Surgeons Constraint

The second constraint that is required to make a scheduling heuristic more realistic is that cases in OR blocks with multiple surgeons operating in the same room on a given day cannot be shifted to earlier or later. Most OR blocks are assigned to a specific surgeons for them to schedule how they desire. If they have time leftover at the end of the day, another surgeon can utilize the room during that time. It would be unlikely that the surgeon that owns the OR block would allow another surgeon to have the first case timeslot and push their cases all to later in the day. Therefore, a constraint is needed to restrict schedule changes to OR blocks with only one surgeon operating or only moving cases within a single surgeon. See Appendix 6.6.2 for details on the logic applied to incorporate this constraint into the analysis.

3.4 Hospital Discharges

The previous scenarios address scheduling changes that staff in the perioperative area could affect but just as important is when patients are discharged from the hospital floor to allow patients to move from the PACU to the floor. These scenarios shift the time a bed was cleaned 5, 15, 30, and 60 minutes earlier. This simulates what the effect would be if the hospital floors were able to discharge all of their patients a set number of minutes earlier in the day.

3.5 Bed Assignment

As discussed in Section 1.3.4 Bed Assignment, each morning admitting works with the hospital floor nursing staff to assign surgical patients to beds that will be coming available for that particular day. Admitting assigns beds based on the scheduled start time of the surgery, starting with the first surgery of the day. Often times a patient will be waiting in the PACU even though there is a hospital bed available that they meet the requirements for because the bed has been previously assigned to another patient. In an effort to see the impact of having dynamic, real-time bed assignments, a final scenario utilizes a first-come-first-serve bed assignment policy.

4 Evaluating Options through Data-Driven Simulation

4.1 Introduction

Realizing that a large part of PACU delays for patients is the resource constraint of hospital beds, a simulation model was built to evaluate options to improve patient PACU wait time. Specifically, the model was used to evaluate various policies and heuristics described in the previous section. Simulation scenario success is judged by the impact on patient PACU wait time and PACU occupancy.

4.2 Methods

4.2.1 Perioperative simulation overview

In order to analyze and compare scheduling policies and patient discharge patterns a discrete event simulation (DES) was used. By using DES, the complex perioperative system was modeled and real patient data used to simulate the current and potential future states of the environment. This simulation was constructed and evaluated using ProModel Corporation's MedModel discrete event simulation software. MedModel is a version of ProModel that is used specifically for hospital applications (ProModel Corporation, 2012).

There are four types of locations in the perioperative process: Center for Perioperative Care, Pre-op and Post-op bays (generally referred to as the Post Anesthesia Care Unit, or PACU), Operating Rooms, and the Hospital Floor (see Figure 8). Patients travel to and stay in each location for the time of their actual stay as recorded in the electronic patient timestamp system. Depending on the patient type, some go to locations once before surgery and return after surgery for different types of processing. Patients' time spent in the PACU after being medically ready to leave was recorded as wait time. Statistics on this metric and occupancy in the peri-op bays were exported and analyzed. Once the baseline model was created, output statistics were validated to ensure accuracy of the model. Various scenarios were run to evaluate the impact on patient flow through the perioperative locations.

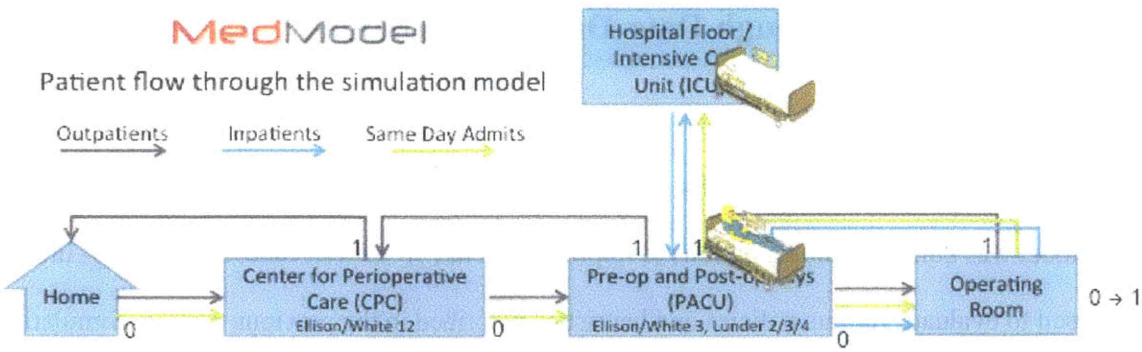


Figure 8: Simulation model patient flow

Inputs include patient information about their journey through the hospital- what steps they go through, how long they spend in each step, when they arrive to the system and hospital bed restrictions. Another key input was bed availability information- what date and time different types of beds became available to take patients. Outputs include when each patient left the system, how long they waited in the PACU, and occupancy throughout the day for each of the process areas. The inputs and outputs to the simulation are summarized below in Table 15 and Table 16.

Simulation inputs	Source of input
Patients' arrival timestamps in modeled units	PACU/OR timestamp data
Patients' length of stay in CPC & PACU	PACU/OR timestamp data
Final hospital floor location, gender, and infectious disease flag	OR PRISM data
Bed assignment	Hospital admitting data
Bed availability through the day	Bed cleaned data

Table 15: Summary of simulation inputs

Simulation outputs	Purpose of output
Census counts for each location with each departure or arrival	Compare simulated to historical values, as well as different scenarios to baseline
Time patients spent waiting in PACU	Compare simulated to historical values, as well as different scenarios to baseline
System departure times for each patient type	Compare simulated to historical values

Table 16: Summary of simulation outputs

Additional details regarding simulation design (locations, entities, processing steps, etc.) are found in Appendix 6.8.

4.2.2 Data preparation

The data for the simulation model is derived from timestamps of each patient's steps through the Center for Preoperative Care (CPC), Pre/post anesthesia Care Unit (PACU), Operating Room (OR) and the Hospital Floor. The data includes operations taking place January 1, 2012 through June 30, 2012. This includes 18,047 surgical and non-surgical cases (including 5,298 Same Day Admits) occurring on weekdays (Monday-Friday) and non-holidays. Only prime-time OR starts are included (operations starting between 8am and 5pm). See Appendix 6.7 for analysis on in-scope and out-of-scope data statistics.

4.2.3 Modeling the Scheduling System

As discussed in Section 0 MGH OR Scheduling System, there are four main components in the system. The model takes each of these four components into account. The following sections describe how each of these items is reflected in the model, what assumptions were made, and shortcomings within each area.

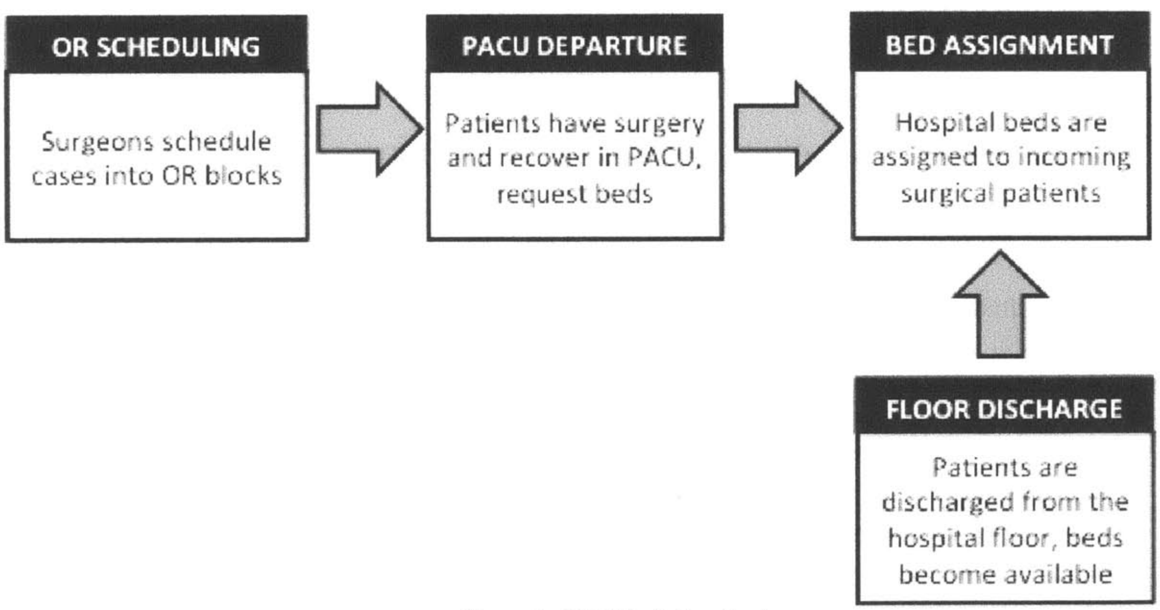


Figure 9: OR Scheduling System

4.2.3.1 Surgeons scheduling OR blocks

The first component in the model creation is simulating the surgeons scheduling cases. If there is only one case during the hours of prime time (8:00AM-5:00PM) then the room is not affected by any scheduling changes. If there are two or more cases in a room, then the order of the cases depends on the scheduling rule being applied. As discussed in Section 3.2 General Heuristics, predicted case length and patient type were attributes that determined the order. Each scheduling scenario was set outside the simulation in an excel database. The model assumes that the length of a given surgery and the room turnover time between surgeries will be the same length even if the operation is shifted in the schedule to begin earlier or later. It also assumes the start time in the room will be the same even if another surgery begins first. An example of how case start times changed based on new ordering in found in Table 17.

Case	Original Order	Original Operation Start Time	Operation Length	Room Turnover Time	New Order	New Operation Start Time
A	1	8:00AM	120 mins	60 mins	**3**	**3:30PM**
B	2	11:00AM	75 mins	45 mins	**2**	**1:30PM**
C	3	1:00PM	240 mins	30 mins	**1**	**8:00AM**

Table 17: Case Reordering Example

4.2.3.2 Perioperative Process

The second component of the model is the perioperative surgical process. The perioperative department records timestamps for each patient as they enter or depart each location. These timestamps are used to model patients flowing through the simulation model.

A transport time is calculated based on the departure from one location in the process flow to the arrival time to the next location in the process flow. As a validation step, all the individual process times added to the start time equals the ending timestamp. For patients that did not go to a particular location, their length of stay (LOS) is set to zero. If patients visit multiple locations in the same category (i.e., PACU pre-op is conducted on the 3rd floor of the Ellison building and 2nd floor of the Lunder building) (see Appendix 6.3 for a map of these locations at MGH), the PACU pre-op time is calculated as the minimum arrival time and maximum departure time for the two locations. In addition to the surgical patients in the model, there are patients that utilize the perioperative bays but do not require use of the operating room.

These non-surgical patients make up 10% of the cases. It is important to include these patients so the model does not underestimate the volume going through the system.

The reordering that happens in the surgical schedule is reflected in a new start time of the patient into the system. This causes patients to need hospital beds at different times of the day and simulate what would have happened if the patient arrived earlier or later.

4.2.3.3 Hospital Floor Discharges

The third component of the model is the hospital floor discharge process. Data was gathered detailing what time the bed each patient went to was finished being cleaned. This is used as the time the bed was actually ready for a new patient.

Each bed-cleaned timestamp corresponds to a patient. It takes on the characteristics of the corresponding patient (floor, gender, and infectious disease flag) as well as what time that patient's bed was cleaned. This finished cleaning time, is the time that the system allows a patient matching the correct characteristics to proceed to the hospital floor. This means that a patient cannot leave the PACU until a bed-cleaned timestamp arrives that matches the floor they need to go to, their gender, and whether or not they have an infectious disease and therefore need a private room.

The simulation uses the time a bed was cleaned on the hospital floor as the trigger for a Same Day Admit to leave the PACU, therefore the wait times in the simulation are actually wait times for a bed to be cleaned. For all other patient types, the length of stay in the PACU is determined by how long the patient actually stayed there historically. In previous iterations of the model, timestamps of when Same Day Admits departed the PACU were used as a conservative estimate of bed availability, knowing that the bed may have been ready earlier, but the limiting factor was the patient's own medical readiness to leave.

Note that due to the complex integration of multiple, never linked together before, databases to derive the bed-cleaned timestamps (links between OR PRISM database, admitting database, and cleaning staff database), 35% of the Same Day Admit patients do not have usable bed cleaned data available. To approximate the time these patient's beds were cleaned, the distribution of bed-cleaned data for the 65% with quality timestamps (i.e., the number of minutes before PACU departure a bed was cleaned) was applied to the patients without BedCleaned data. A graph of the distribution is found below.

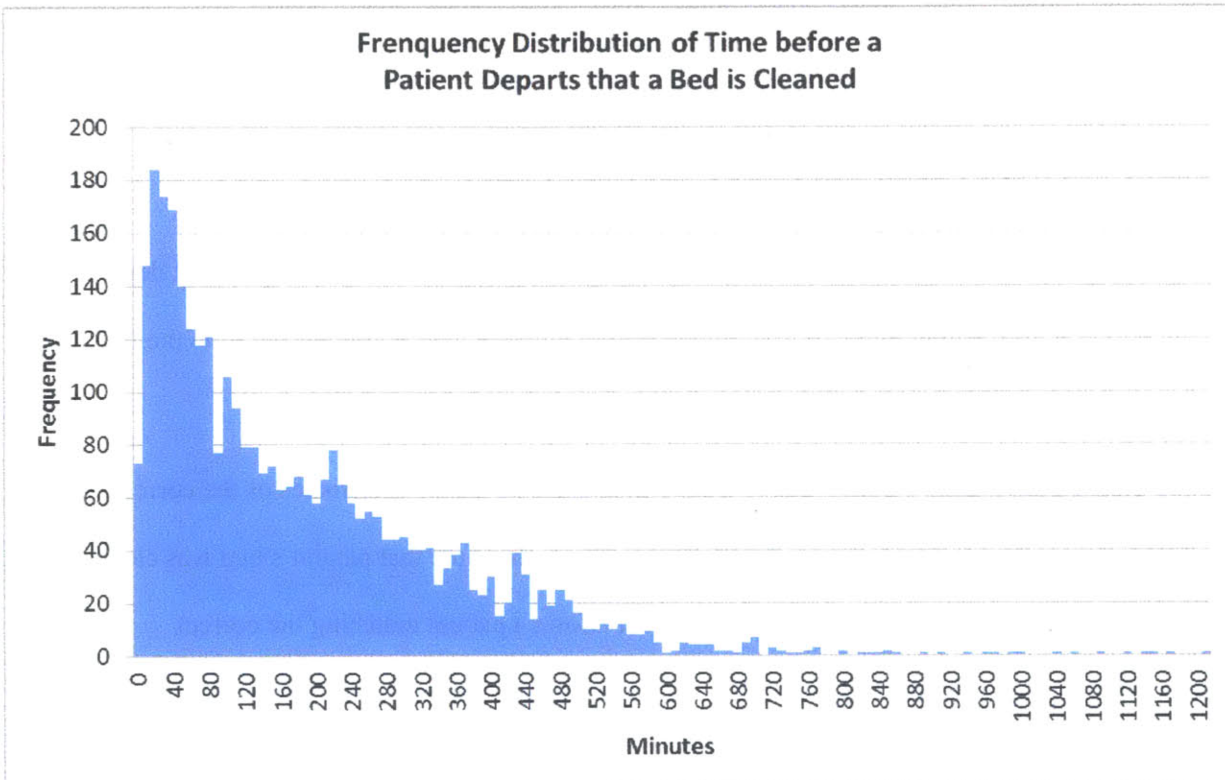


Figure 10: Frequency distribution of bed-cleaned data

4.2.3.4 *Admitting Bed Assignment*

The final component represented in the model is the assignment of beds to surgical patients. It is assumed that as soon as a bed that meets certain restrictions arrives it goes to the patient that has been waiting the longest (i.e., the first patient to be medically ready to depart). The bed-cleaned timestamps are not specific to a single patient (i.e., a patient doesn't have to go back to the same bed that went to in "real life") but they are specific for a patient's gender, infectious disease flag, and hospital floor. Most rooms at MGH are semi-private and have the restriction that patients sharing a room be the same gender; this is why these bed-cleaned timestamps must be gender-specific. Patients that have an infectious disease must be placed in a private room or the second bed in a semi-private room must remain empty. Each surgical specialty (Orthopedic, Thoracic, Neurosurgery, etc.) keeps their patients on a particular floor (or floors) in the hospital.

Details regarding floor numbering and methodology used can be found in Appendix 6.10.

4.3 Results

4.3.1 Baseline Validation

To ensure the simulation model is operating as expected, the baseline of what actually occurred January through June of 2012 is validated. The first three metrics validated by entity type are system exits (number of patients coming in and leaving the simulation), average time in the system, and average time in operation. System exits ensure that the number of patients that went into the simulation go through the entire model and exit the system. Average time in the system compares the patient's actual start and end times to the total time of the entity type in the simulation. Average time in operation compares the sum of the patient's length of stay in each location to the processing time of the entity type in the simulation. All three metrics were validated as seen in the tables below.

System Exits	MGH Actuals	Simulation Model	Delta
Outpatient	6494	6494	0.00%
SameDayAdmit	5394	5394	0.00%
Inpatient	4943	4943	0.00%
NonOR	1893	1893	0.00%
SDAOther	1399	1399	0.00%
BedNotification	5394	5394	0

Table 18: System exits validation

Average Time In System (Min)	MGH Actuals	Simulation Model	Delta
Outpatient	437	437	0.00%
SameDayAdmit	577	577	0.00%
Inpatient	339	339	0.00%
NonOR	156	156	0.00%
SDAOther	898	898	0.00%
BedNotification	-	-	-

Table 19: Average time in the system validation

Average Time In Operation (Min)	MGH Actuals	Simulation Model	Delta
Outpatient	389	389	0.00%
SameDayAdmit	480	480	0.00%
Inpatient	336	336	0.00%
NonOR	149	149	0.00%
SDAOther	857	857	0.00%
BedNotification	-	-	-

Table 20: Average time in operation validation

The next metric validated is the time of system departures by entity type. The expected departure time for each individual entity is compared to the actual departure times of all the entities[3]. 100% of the system departure times were within one minute of the expected time. The results of this validation are found in the table below.

Comparison of System Departure Times	Avg Delta	Min Delta	Max Delta	Sum of the Deltas	Number of Deltas between -1 and 1 minute	Total Number of Entities	Percent of Deltas between -1 and 1 minute
Outpatient	0	-	0	0	6,494	6494	100.00%
SameDayAdmit	0	-9	1	-7	5,393	5394	100.00%
Inpatient	0	-1	0	-263	4,943	4943	100.00%
SDAOther	0	-1	0	-3	1,399	1399	100.00%
NonOR	0	0	0	0	1,893	1893	100.00%
BedNotification	0	0	1	2	5,394	5394	100.00%

Table 21: System departure time validation

Another metric that is validated the occupancy of each location. The weighted average difference of the expected and simulation occupancy levels is compared in the table below.

Occupancy Levels by Location	Expected Weighted Average Occupancy	Simulation Weighted Average Occupancy	Delta	Percent Delta
CPC	5.47	5.42	-0.04	-1%
PACU	16.44	15.83	-0.62	-4%
OR	11.52	11.48	-0.04	0%

Table 22: Occupancy levels validation

[3] The difference between these two numbers is the "delta".

The remaining differences in location occupancy can be attributed to overlapping timestamps that were adjusted before going into the model. An example of this adjustment can be found in Table 23. This patient spent 77 minutes in Lunder 4 (a peri-op PACU location) but 'arrived' to the operating room 11 minutes before they departed Lunder 4. In this case their pre-op PACU time is adjusted to be 66 minutes instead of 77 minutes. Cases that have this data abnormality account for the differences in actual and simulation occupancy levels.

Arrive at Lunder 4	Depart Lunder 4	Arrive at OR	Depart OR
6:39 AM	7:56 AM	7:45 AM	2:21 PM

Table 23: Example of timestamp adjustment

Of particular interest is the peri-op bay occupancy. The simulation provides a level of detail not previously viewed at MGH so to ensure the model's accuracy an experiment was run. Peri-op bay levels found in the OR PRISM database are recorded three times a day at approximately 10:00 AM, 2:00 PM, and 4:00 PM for one week and then compared to the average occupancy in the model for that time of day and day of week. Figure 11 is an example of the PRISM system displaying the number of occupied slots in the peri-op areas.

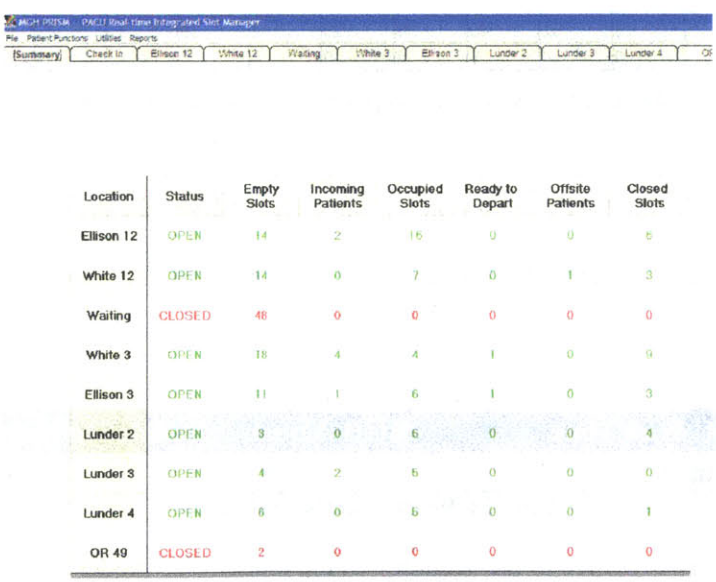


Figure 11: PRISM occupied slots

Figure 12 displays the results from the experiment. In 15 out of the 26 cases the model was within two patients of the weekday average at that time. Outliers such as Wednesday, June 20th at 5:00 PM and Friday, June 22nd at 4:00 PM are to be expected as the model took an average for each weekday over three months of data. See Appendix 6.12 for peri-op bay occupancy graphs including the 5th, 95th, average, and max of each weekday over three months. Data used was January 2012 through March 2012 from the OR PRISM database.

Test Day:	Tues, June 19	Wed, June 20	Wed, June 20	Wed, June 20	Thurs, June 21	Thurs, June 21	Thurs, June 21	Fri, June 22	Fri, June 22	Fri, June 22	Mon, June 25	Mon, June 25	Tues, June 26
Time:	4PM	10AM	2PM	5PM	10AM	2:30PM	4PM	10AM	2:10PM	4PM	10AM	3PM	10AM
E12	7	16	3	16	14	12	8	11	9	3	10	6	16
W12	0	6	1	6	3	0	0	5	0	0	8	0	7
CPC Total	**7**	**22**	**4**	**22**	**17**	**12**	**8**	**16**	**9**	**3**	**18**	**6**	**23**
W3	15	7	17	7	3	14	16	8	18	10	4	14	4
E3	13	10	14	10	6	8	7	9	13	6	8	10	6
L2	3	3	1	3	0	4	5	7	4	5	4	5	6
L3	5	6	5	6	1	5	2	6	3	3	7	2	5
L4	7	6	3	6	5	7	5	3	4	4	3	3	5
PACU Total	**43**	**32**	**40**	**32**	**15**	**38**	**35**	**33**	**42**	**28**	**26**	**34**	**26**
Grand Total	***50***	***54***	***44***	***54***	***32***	***50***	***43***	***49***	***51***	***31***	***44***	***40***	***49***

CPC - E12, W12

PRISM Occupied Slots on Test Days	7	22	4	22	17	12	8	16	9	3	18	6	23
Model Occupancy for Weekday*	6	22	9	3	17	10	7	21	9	6	20	6	23
Difference	-1	0	5	-19	0	-2	-1	5	0	3	2	0	0

PACU - W3, E3, L2/3/4

PRISM Occupied Slots on Test Days	43	32	40	32	15	38	35	33	42	28	26	34	26
Model Occupancy for Weekday*	43	32	45	35	15	42	39	35	45	40	26	36	31
Difference	0	0	5	3	0	4	4	2	3	12	0	2	5

Figure 12: Peri-op bay occupancy level experiment results

The final metric validated is the PACU wait time of Same Day Admits for the current state baseline. Using timestamps for when hospital beds were finished being cleaned, the wait time comparison is as follows:

PACU Wait Time	MGH Actuals	Simulation Model	Delta
SameDayAdmit	24.85	24.85	0.00%

Table 24: PACU wait time validation

These validated metrics are evidence to the accuracy of the model. The model may now be reasonably used to predict the system's response to potential future scenarios. The following sections outline the results of these scenarios.

4.3.2 General Heuristics

Various scenarios were run in the simulation model to test their impacts without having to commit to changes in the actual system. The results of the scenarios were compared with the baseline of wait time between PACU Ready to Bed Cleaned. See Table 25, Table 26, and Figure 13 for scenario results.

The longest cases first scenario has the longest wait times. This is due to scheduling the more complex (and therefore longer) cases that will need beds first in the day. Those patients arrive earlier to the PACU and do not allow the hospital floor staff adequate time to discharge their patients. The shortest cases first scenario has lower wait times than the longest cases first scenario. Because the length of surgery scenarios are some of the longer scenarios, this means that length of surgery is not a relevant as other factors in lowering wait times.

The outpatient first scenario has shorter wait times than the length-based scenarios, however, this scenario has a downside in that by default of Outpatients being scheduled first, the Inpatients and SameDayAdmit patient categories get mixed together and are scheduled last. We are only concerned with the SameDayAdmits as they will need beds they do not have yet. The next scenario will try to capture this.

The SameDayAdmits (SDA) last scenario has improved wait times from the Outpatients first scenario. It has a 54% improvement in wait time. There are two other MGH patient categories that start at home and need a bed at the end of the day. These are Observation and RPPR the patients.

The SameDayAdmits, Observation, RPPR Last scenario incorporates the two additional patient categories and schedules them last in the operating schedule. This is the best scenario as it schedules all patients that will most likely need a bed at the end of the day last. It gives the hospital floors the maximum time possible to get their patients discharged so surgical patients don't have to wait an extended amount of time in the PACU. This scenario also has the biggest impact on the outliers in the system. The 90^{th} quantile of patients were waiting longer than 94 minutes for a bed. In this final scenario, the 90^{th} quantile was reduced to just 9 minutes, a 90% reduction in wait time. One other potential benefit of this scenario is that by scheduling patients that will need a bed after surgery last, you are scheduling patients that won't need a bed after surgery first. This includes inpatients that are already in the hospital. This may also improve on-time first case starts as you would be taking out some of the variability caused by the admitting processes in the morning for same day admits before the first case starts.

Statistics on the wait time for a bed to be cleaned are found below in Table 25. (Note that these wait time statistics do not include the wait time due to communication and processing delays. This wait time only includes delays due to bed availability. See Section 2.3.3 Current State Wait Time Analysis for more details.)

Wait Time Analysis	Baseline	Shortest Cases First	Longest Cases First	Outpatients First	SDA Last	SDA/OB/RR Last	Random
Mean	25	17	22	13	12	10	20
Maximum	661	527	509	527	527	527	559
85% Quantile	47	12	47	-	-	-	34
90% Quantile	94	56	84	34	21	9	76
95% Quantile	171	125	146	95	82	71	145
Standard Deviation	67	54	58	45	44	39	57
% Not Waiting	78%	83%	77%	86%	87%	89%	80%
% Waiting	22%	17%	23%	14%	13%	11%	20%
Avg of the longest 22%	115	79	102	58	53	44	93
Avg of Patients that Wait	115	104	96	88	89	87	101

Table 25: General heuristics scenario results statistics

Figure 13 displays graphically the reduction in wait time for the 22% of Same Day Admits that wait for a bed in the baseline.

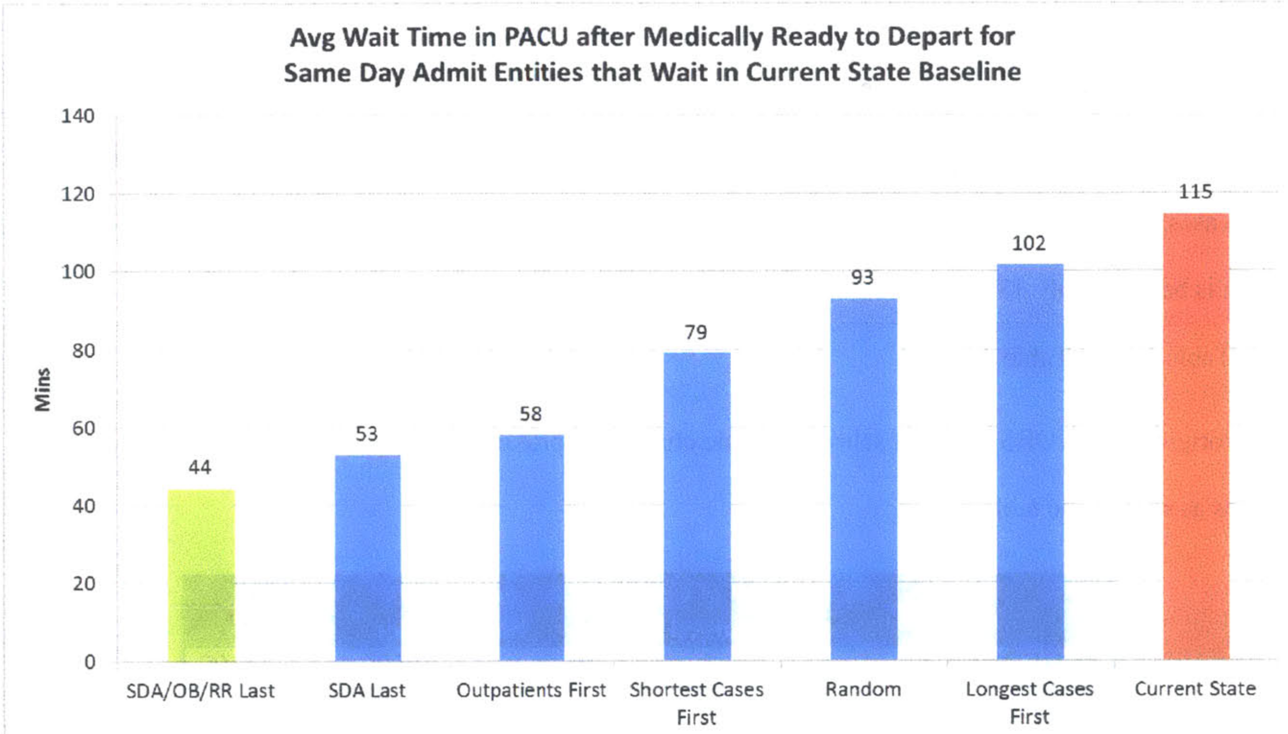


Figure 13: General heuristic scenarios comparison

Statistics on the wait time for a bed to be cleaned versus the baseline are found below:

	Baseline					
Wait Time Analysis	Shortest Cases First	Longest Cases First	Outpatients First	SDA Last	SDA/OB/RR Last	Random
Mean	-31%	-11%	-49%	-54%	-61%	-19%
Maximum	-20%	-23%	-20%	-20%	-20%	-15%
85% Quantile	-74%	0%	-100%	-100%	-100%	-28%
90% Quantile	-40%	-11%	-64%	-78%	-90%	-19%
95% Quantile	-27%	-15%	-44%	-52%	-58%	-15%
Standard Deviation	-20%	-14%	-34%	-35%	-42%	-15%
% Not Waiting	7%	-2%	9%	11%	13%	2%
% Waiting	-24%	7%	-34%	-40%	-49%	-8%
Avg of the longest 22%	-31%	-11%	-49%	-54%	-61%	-19%
Avg of Patients that Wait	-10%	-17%	-23%	-23%	-24%	-12%

Table 26: General heuristic scenario results versus baseline

4.3.3 Scheduling Constraints

The most optimal scenario from the general scheduling heuristics, SameDayAdmits, Observation, RPPR Last scenario, was made more realistic by incorporating two constraints. The result of adding in each constraint was compared to the baseline. The constraints reduce the number of cases that can be moved around to optimally schedule the patients. With each additional constraint the wait time for patients increases. The surgeon constraint has a bigger impact on the wait time than the waitlist constraint does. That is because only 13% of the cases are moved versus 18% moved in the waitlist constraint (see Table 27, Table 28 and Table 29).

The original SDA/OBS/RR Last scheduling rule changes approximately 26% of the cases operating start times as seen in the table below.

	# of Cases Changed Order	# of Cases Same Order	Total
SCHEDULED	3603	10506	14109
WL/EMERGENT	25	61	86
WL/NON-URGENT	529	1205	1734
WL/URGENT	80	166	246
Grand Total	4237	11938	16175
Percent of Total	26%	74%	100%

Table 27: SDA/OBS/RR Last scenario impact on number of cases changed

Once the waitlist case constraint is applied, the 26% of cases affected goes down to 18% of cases that have a start time moved to implement the new schedule as seen below.

	# of Cases Changed Order	# of Cases Same Order	Total
SCHEDULED	2908	11201	14109
WL/EMERGENT	0	86	86
WL/NON-URGENT	0	1734	1734
WL/URGENT	0	246	246
Grand Total	2908	13267	16175
Percent of Total	18%	82%	100%

Table 28: Waitlist constraint impact on number of cases changed

The multiple surgeon constraint reduces the percent of cases affected to 13%. The number of cases that have a start time moved to implement the new schedule is below.

	# of Cases Changed Order	# of Cases Same Order	Total
One Surgeon	1928	7541	9469
No Changes		4098	4098
Surgeons Switched		2403	2403
Cases switched within one surgeon	125	80	205
Grand Total	**2053**	**14122**	**16175**
Percent of Total	13%	87%	100%

Table 29: Multiple surgeon constraint impact on number of cases changed

When the constraints are combined the wait time reduction goes from 61% to 49% versus current state. See Table 30, Table 31, and Figure 14 for details around this decrease in wait time improvement. Statistics on the wait time for a bed to be cleaned are found below:

Wait Time Analysis	Baseline	SDA/OB/RR Last	Multiple Surgeon Constraint	Waitlist Constraint	Multiple Surgeon & Waitlist Constraints
Mean	25	10	12	11	13
Maximum	661	527	527	527	527
90% Quantile	94	9	29	22	35
95% Quantile	171	71	90	83	95
Standard Deviation	67	39	44	42	45
% Not Waiting	78%	89%	86%	87%	85%
% Waiting	22%	11%	14%	13%	15%
Avg of the longest 21.7%	115	44	56	52	59

Table 30: SDA/OB/RR Last scenarios result statistics

Figure 14 displays graphically the average wait time for the longest waiting 22% of SameDayAdmits (the patients that waited in Baseline) for each constraint addition and the combination of the two constraints.

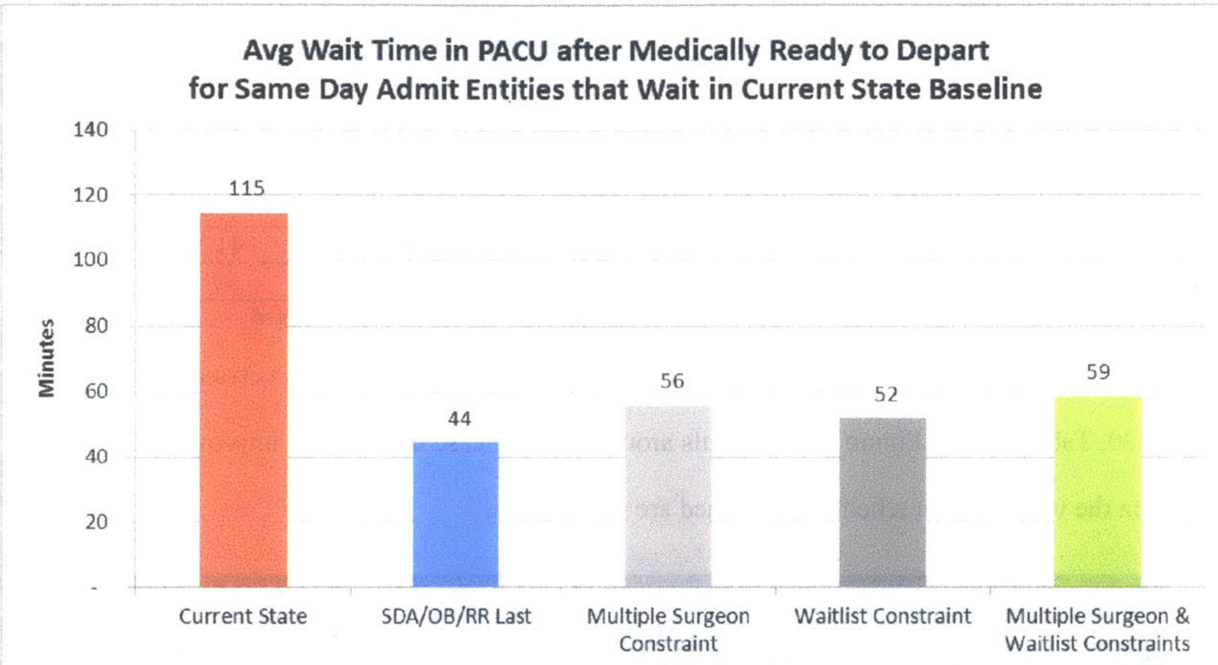


Figure 14: SDA/OB/RR Last scenarios comparison

Statistics on the wait time for a bed to be cleaned versus the baseline are found below:

	Baseline			
Wait Time Analysis	SDA/OB/RR Last	Multiple Surgeon Constraint	Waitlist Constraint	Multiple Surgeon & Waitlist Constraints
Mean	-61%	-51%	-55%	-49%
Maximum	-20%	-20%	-20%	-20%
90% Quantile	-90%	-69%	-77%	-63%
95% Quantile	-58%	-47%	-51%	-44%
Variance	-66%	-57%	-61%	-56%
Standard Deviation	-42%	-34%	-37%	-33%
% Not Waiting	13%	10%	11%	9%
% Waiting	-49%	-35%	-40%	-32%
Avg of the longest 21.7%	-61%	-51%	-55%	-49%

Table 31: SDA/OB/RR Last scenario results versus baseline

These constraints reduce the number of cases and operating rooms affected by the SDA/OBS/RR Last scheduling rule to 10%. The number of cases that have a start time moved (organized by the multiple surgeon constraint) to implement the new schedule is below.

	# of Cases Changed Order	# of Cases Same Order	Total
One Surgeon	1479	7990	9469
No Changes		4098	4098
Surgeons Switched		2403	2403
Cases switched within one surgeon	91	114	205
Grand Total	1570	14605	16175
Percent Total	10%	90%	100%

Table 32: Combined constraints impact on number of cases changed

The following table compares how adding each constraint changes the number of operating room/days affected.

# of Operating Rooms	Changed	Same	Total	% Changed
Current State	0	6538	6538	0%
SDA/OB/RR Last	1647	5327	6538	25%
Waitlist Constraint	1166	5791	6538	18%
Multiple Surgeons Constraint	804	6001	6538	12%
Combined Constraints	629	6157	6538	10%

Table 33: Combined constraints impact on number of OR blocks changed

Similarly, the table below compares how adding each constraint changes the number of cases affected.

# of Cases	Changed	Same	Total	% Changed
Current State	0	16175	16175	0%
SDA/OB/RR Last	4237	11938	16175	26%
No WL	2908	13267	16175	18%
No Surgeon	2053	14122	16175	13%
No WL or Surgeon	1570	14605	16175	10%

Table 34: Summary of scenarios impact on number of cases changed

In summary, scheduling Same Day Admits, Observation, and RPPR patients last, with the waitlist and multiple surgeon constraints incorporated, only affects 10% of the cases but reduces wait time for those patients by 49%.

4.3.4 Earlier Hospital Discharges

The results of discharging patients in hospital floor beds earlier were compared to the current state baseline. Discharging patients in hospital beds 60 minutes earlier leads to a 42% reduction in wait time and discharging patients 30 minutes earlier leads to a 23% reduction in wait time. Even discharging patients five minutes earlier makes an impact on the 22% that wait in the current state baseline as almost that entire population waits at least five minutes.

Statistics on the wait time for a bed to be cleaned are found below:

Wait Time Analysis	Baseline	Discharge 5 minutes earlier	Discharge 15 minutes earlier	Discharge 30 minutes earlier	Discharge 60 minutes earlier
Mean	25	24	22	19	14
Maximum	661	656	646	631	601
85% Quantile	47	42	32	17	-
90% Quantile	94	89	79	64	34
95% Quantile	171	166	156	141	111
Variance	4,544	4,360	3,996	3,497	2,651
Standard Deviation	67	66	63	59	51
% Not Waiting	78%	79%	81%	83%	87%
% Waiting	22%	21%	19%	17%	13%
Avg of the longest 21.7%	115	110	101	88	67

Table 35: Discharge scenarios result statistics

Figure 15 displays graphically the average wait time for all SameDayAdmits and for the longest waiting 22% of SameDayAdmits (the patients that waited in Baseline) with earlier discharges by 5, 15, 30, and 60 minutes.

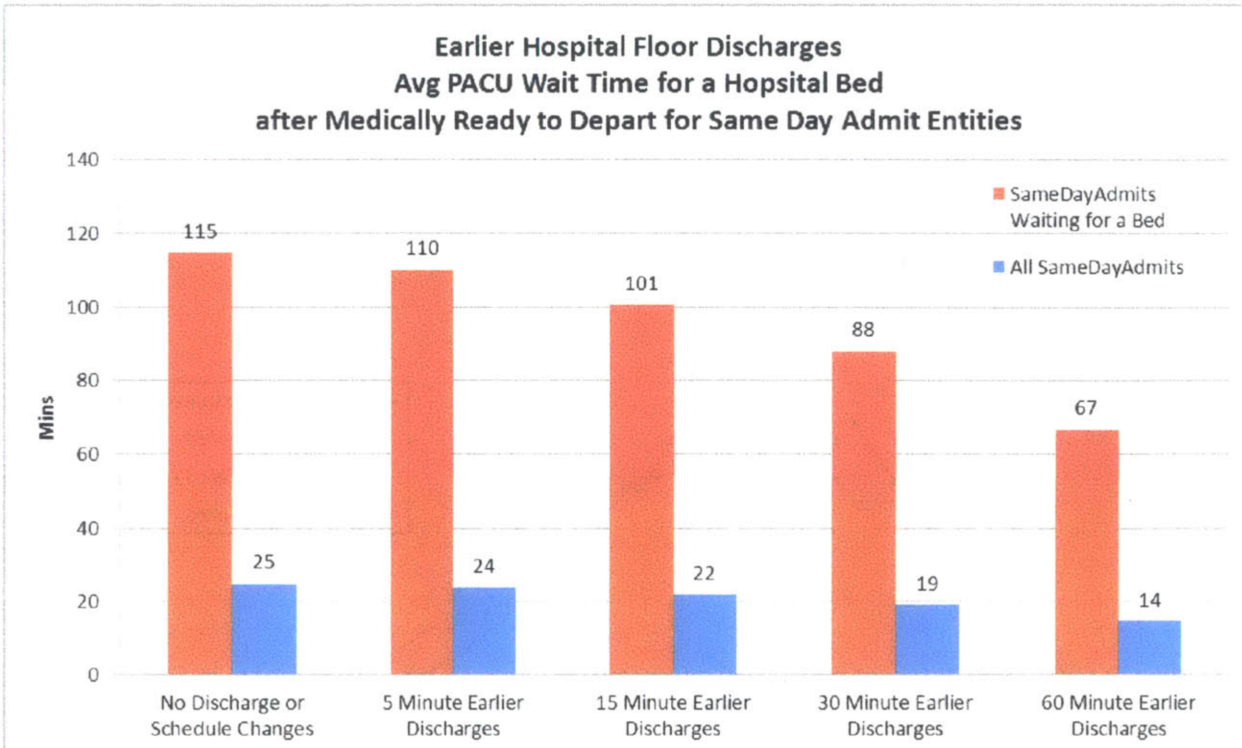


Figure 15: Discharge scenarios comparison

Statistics on the wait time for a bed to be cleaned versus the current state baseline are found below:

	Baseline			
Wait Time Analysis	Discharge 5 minutes earlier	Discharge 15 minutes earlier	Discharge 30 minutes earlier	Discharge 60 minutes earlier
Mean	-4%	-12%	-23%	-42%
Maximum	-1%	-2%	-5%	-9%
85% Quantile	-11%	-32%	-64%	-100%
90% Quantile	-5%	-16%	-32%	-64%
95% Quantile	-3%	-9%	-18%	-35%
Variance	-4%	-12%	-23%	-42%
Standard Deviation	-2%	-6%	-12%	-24%
% Not Waiting	1%	3%	6%	10%
% Waiting	-3%	-10%	-20%	-38%
Avg of the longest 21.7%	-4%	-12%	-23%	-42%

Table 36: Discharge scenario results versus baseline

Figure 16 shows by hour of the day the number of patients ready to leave the PACU versus the number of beds cleaned in the current state baseline, 30 minutes earlier discharges, and 60 minute earlier discharges. The 60 minute earlier discharges better matches the needs of the PACU for hospital beds.

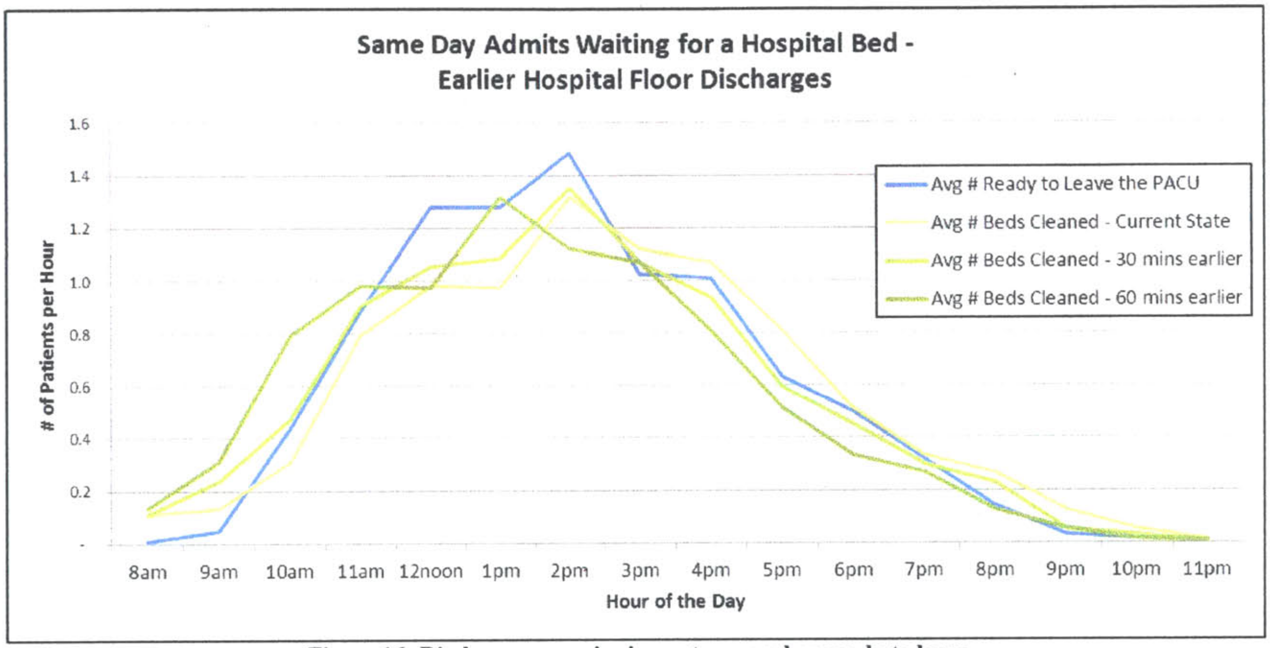


Figure 16: Discharge scenarios impact on number ready to leave

4.3.5 Bed Assignments

The baseline is run again, but this time with allowing patients to go to beds as they come available, not necessarily the bed they actually went to. Without any scheduling changes, just more efficient bed assignments, the wait time for a bed is reduced by 41%. Results for this scenario are found below:

Wait Time Analysis	Baseline	First Come First Serve Beds	% Change
Mean	25	14.7	-41%
Maximum	661	527	-20%
90% Quantile	94	49	-48%
95% Quantile	171	108	-37%
Standard Deviation	67	47	-30%
% Not Waiting	78%	83%	6%
% Waiting	22%	17%	-22%
Avg of the longest 22%	115	68	-41%
Avg of Patients that Wait	115	88	-24%

Figure 17: Bed assignment scenario results

5 Final Recommendations

5.1 Summary of Recommendations

There are four key recommendations for MGH:

1. Work on assigning beds on a first come first serve basis, assuming the patients meet the requirements for the bed. Admissions staff should assign beds at the beginning of the day according to each patient's operation expected end time not the operation start time. By reducing this inefficiency in the system, patients would not need to wait for beds when one is actually available.
2. MGH should work with each surgical specialty to request they schedule Same Day Admits, Observation, and RPPR patients last in each operating room block. By communicating the benefits of reduced waiting time for their patients, surgeons should be motivated to schedule their patients in this way.
3. The perioperative department should work to reduce time between when a bed is cleaned and when a patient can go to the floor with improved nursing communication and processing. By understanding which steps need to happen when and by whom, patients could move from the PACU to the hospital floor in a more efficient manner.
4. Encourage and empower the hospital floor staff to discharge their patients more strategically. By giving the floor staff data on how many patients need to be discharged by when, staff could set discharge goals each day that improve patient wait times.

5.2 Additional Considerations

There are several additional considerations when thinking about implementing these recommendations. The first is that the PACU is not the only source of demand for hospital beds. Other areas are constantly requesting beds at the same time as well, including the emergency department, the catheterization laboratory, the medicine department, the ICU, front door admissions, and other departments. A more holistic study that incorporates these other departments would be beneficial before implementing change.

Second, there is the potential that by affecting when a patient arrives to a floor you could be shifting the current discharge patterns. For example, if a patient needs 24 hours to recover, if they now arrive to the floor at 6:00PM instead of 3:00PM, they will now discharge the following day at 6:00PM instead of 3:00PM, changing the pattern of discharges for the floor. This would then eliminate the wait time benefit of shifting the schedule. A study would need to be conducted to test whether or not this effect exists.

Third, the current constraint in the model of not allowing waitlist patients to be moved around in the schedule could be removed with other operational changes. These might include having waitlist placeholders in the schedule that would allow the OR Administrator the flexibility to still schedule same day admits last in the day.

Finally, and potentially most importantly, within the hospital there exists politics and a sense of hierarchical power. Simply knowing the best solution for scheduling patients will not be enough to make a change, it will ultimately take convincing surgeons to change their schedules and floor nurses to discharge their patients at a different time which can be far more difficult than just finding the optimal solution.

5.3 Future MIT-MGH Projects

As mentioned in the previous section, there are additional opportunities for improvement that exist at MGH. Follow-on projects to this one might include predicting what time a patient will need a bed for better hospital floor discharge planning, creating an optimization tool that rearranges operating room schedule with historical discharge patterns, and giving the floors guidelines on what percent of patients they need to discharge each hour by day of week. These would all be excellent projects for future MIT-MGH operations research study.

5.4 Conclusion

As one would expect from one of the pre-eminent healthcare institutes in the nation, there exists at MGH a wealth of talent and knowledge. In the operating rooms, miracles are commonplace - every day patient's lives are saved, and for others the quality of life is dramatically improved. One of the features that sets MGH apart as an institution is that, in addition to their medical expertise, the leadership of MGH also strive to be leaders in the efficient delivery of healthcare to patients. In an ever-changing regulatory, governmental, and financial environment, MGH must continue to adapt to meet the needs of the thousands of patients that require its services each year. This study and other research undertaken by the MIT-MGH partnership will help MGH maintain its position not only as a world-leader in medical advancements, but also as the standard-bearer of operational excellence in healthcare.

6 Appendix

6.1 Perioperative Areas and Capacities

Capacities

Center for Perioperative Care (CPC) – '12s' Ellison/White

- Ellison 12 – 34 beds
- White 12 – 22 beds

Induction Rooms – Legacy ORs

- 42 induction rooms, 1 for each operating room

Peri-operative bays – Lunder 2/3/4

- 2nd floor- 13 bays
- 3rd floor- 9 bays
- 4th floor-12 bays

Legacy ORs

- 42 Operating rooms - Numbers 1-49

Lunder ORs

- 2nd floor- 4 ORs (Numbers 51,52,53,54)
- 3rd floor- 13 ORs (Numbers in the 60s,70s)
- 4th floor- 11 ORs (Numbers in the 80s,90s)

Ellison/White 3 PACU

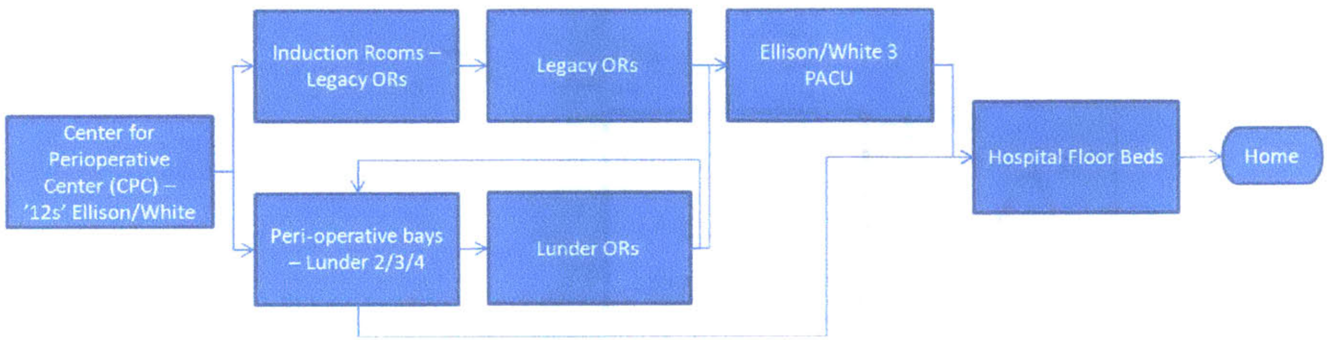
- White 3- 28 beds (serving ORs 1-49, 60s, 70s, and ECT)
- Ellison 3- 20 beds (serving Overflow from White, Pediatrics, and Overnight patients)

Hospital Floor Beds

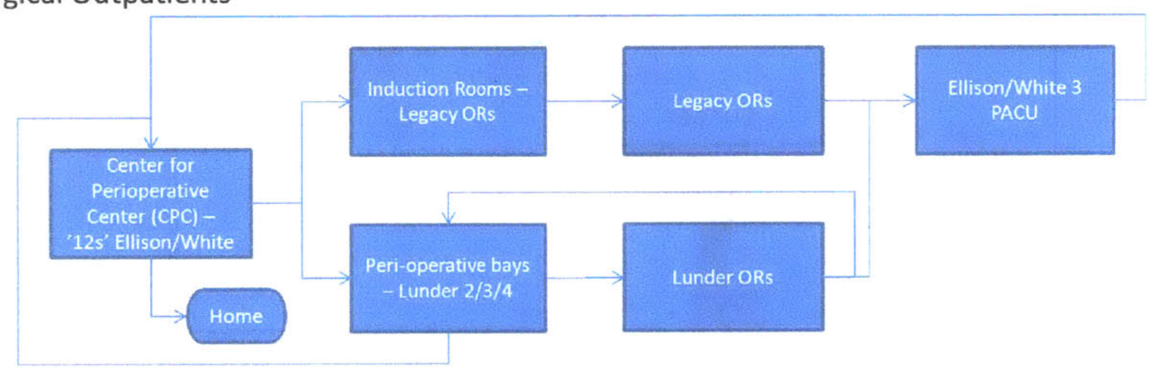
- Blake 06- 21 beds
- Ellison 07- 36 beds
- White 07- 27 beds
- Ellison 08- 36 beds
- Ellison 19- 30 beds
- Bigelow 07- 18 beds
- Bigelow 13- 23 beds
- Bigelow 14- 27 beds
- Lunder 07- 32 beds (Neuro)
- Lunder 08- 32 beds (Neuro)
- Ellison 06- 36 beds (Ortho/Urology)
- White 06- 30 beds(Ortho/Urology)
- Philips 22- 19 beds

6.2 Perioperative Patient Flow

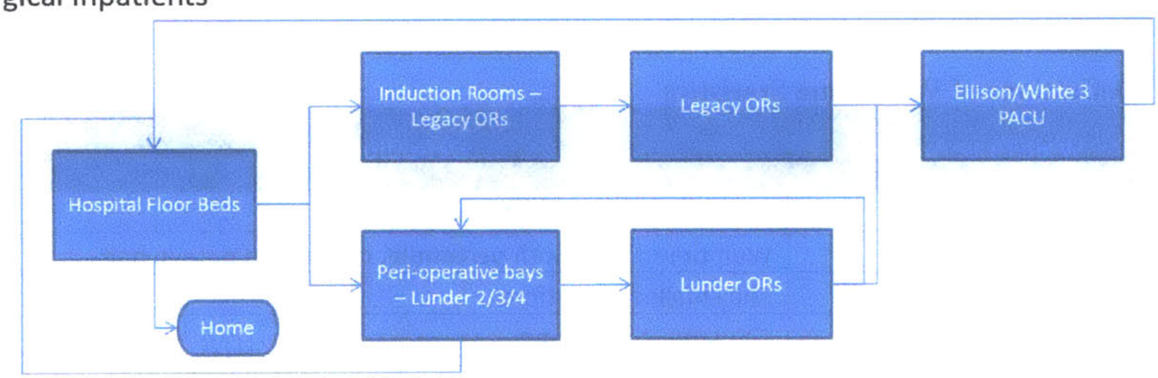
Surgical Same-Day Admits
& RPPR/OBS



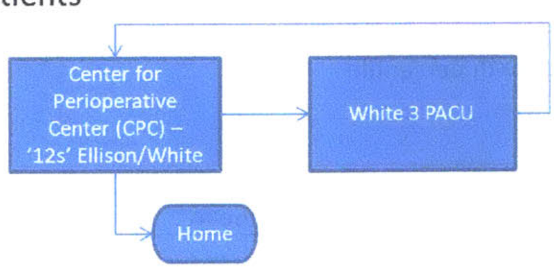
Surgical Outpatients



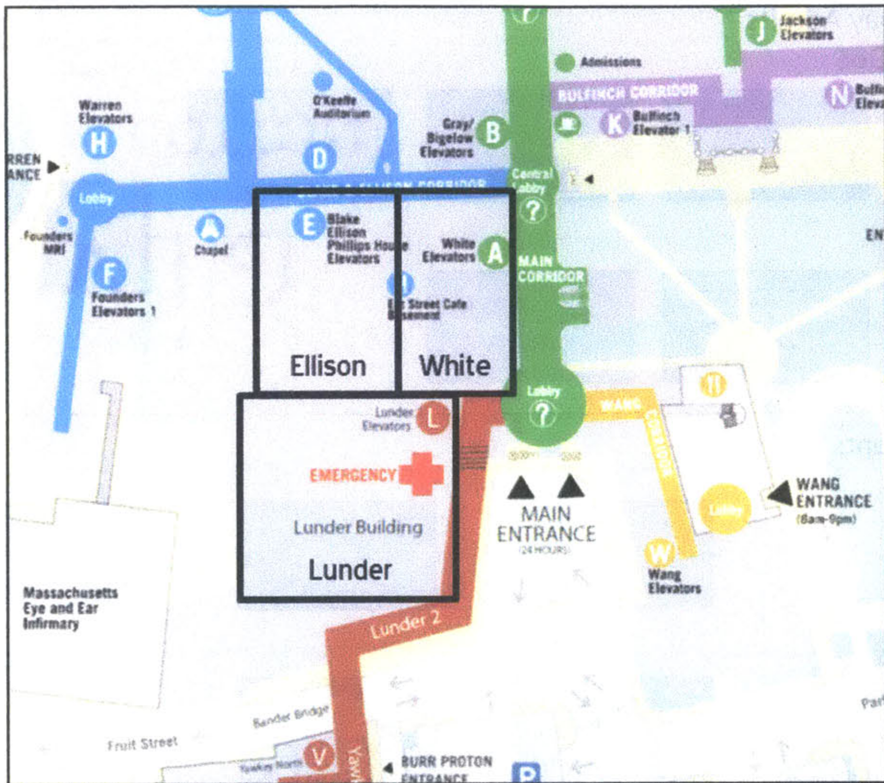
Surgical Inpatients



ECT Patients



6.3 Map of MGH



6.4 Definitions of Wait Time Statistics

Wait Time Analysis	Definition
Mean	Average of all the wait times
Median	Wait time at the 50th percentile, cutting the data in half
Minimum	The smallest wait time
Maximum	The largest wait time
25% Quantile	Wait time at the Xth percentile
50% Quantile	
75% Quantile	
85% Quantile	
90% Quantile	
95% Quantile	
Standard Deviation	How much variation exists around the mean
% Not Waiting	Percent of patients that did not wait
% Waiting	Percent of patient that did wait
Avg of the longest 22%	Average of the longest 22% of wait times
Avg of Patients that Wait	Average of the wait times for those that wait

6.5 Benefits of Heuristics (Gigerenzer, 2008)

Six Common but Erroneous Beliefs About Heuristics

Six common misconceptions	Clarifications
1. Heuristics produce second-best results; optimization is always better.	In many situations, optimization is impossible (e.g., computationally intractable) or less accurate because of estimation errors (i.e., less robust; see investment example).
2. Our minds rely on heuristics only because of our cognitive limitations.	Characteristics of the environment (e.g., computational intractability) and of the mind make us rely on heuristics.
3. People rely on heuristics only in routine decisions of little importance.	People rely on heuristics for decisions of both low and high importance. See investment and organ donation examples.
4. People with higher cognitive capacities employ complex weighting and integration of information; those with lesser capacities use simple heuristics (related to Misconception 1).	Not supported by experimental evidence (e.g., Bröder, 2003). Cognitive capacities seem to be linked to the adaptive selection of heuristics and seem less linked to the execution of a heuristic. See also the Markowitz example in this article.
5. Affect, availability, causality, and representativeness are models of heuristics.	These terms are mere labels, not formal models of heuristics. A model makes precise predictions and can be tested, such as in computer simulations.
6. More information and computation is always better.	Good decisions in a partly uncertain world require ignoring part of the available information (e.g., to foster robustness). See the investment example in this article.

6.6 Model Implementation of Constraints

6.6.1 Waitlist Constraint

The table below summarizes the logic that is applied to implement the waitlist constraint into the model.

Cases within an Operating Room/Day	Schedule Order to Use	# of OR Blocks	Percent of OR Blocks
All scheduled cases (non-waitlist)	Use rescheduled order from the SDA/OBS/RR last scenario	4984	76%
All waitlist cases	Revert to original order	401	6%
Mixed schedule/waitlist case rooms but only one waitlist case and it is the last case in the room	Leave waitlist case at the end and reschedule the cases prior to it	465	7%
All other mixed scheduled/waitlist case rooms	Revert to original order	124	2%
No changes made to the schedule	Keep original order	564	9%
Total		**6538**	**100%**

Table 37: Waitlist constraint logic

6.6.2 Multiple Surgeon Constraint

The table below summarizes the logic that is applied to implement the multiple surgeon constraint into the model.

Cases within an Operating Room/Day	Schedule Order to Use	# of Operating Room/Days	Percent of Operating Rooms
Only one surgeon in the room	Use rescheduled order from the SDA/OBS/RR Last scenario	4221	65%
No changes made to the schedule	Keep original order	1418	22%
Multiple surgeons in the room and two or more surgeons switched case order	Revert to original order	843	13%
Multiple surgeons in the room and switching of cases within one surgeon	Use rescheduled order from the SDA/OBS/RR last scenario	56	1%
Total		**6538**	**100%**

Table 38: Multiple surgeon constraint logic

6.7 In-Scope & Out-of-Scope Data

Summary of in- and out-of-scope data

Summary	Number of Patients	Percent of Patients
In-Scope	18047	89.68%
Out-of-Scope	2076	10.32%
Grand Total	20123	100.00%

Patients with operations occurring on a Saturday or Sunday are considered out-of-scope.

Weekends	Number of Patients	Percent of Patients
Weekday	19232	95.57%
Weekend	891	4.43%
Grand Total	20123	100.00%

Patients with operations occurring on a holiday are considered out-of-scope.

Holidays	Number of Patients	Percent of Patients
Holiday	55	0.27%
Non-Holiday	20068	99.73%
Grand Total	20123	100.00%

Patients with operations occurring outside of prime-time (Into OR timestamp is between 5:00PM and 7:00AM) are considered out-of-scope. Note that all Non-OR cases are assumed to be in-scope regardless of their start times. These cases are all electively scheduled non-surgical procedures that use the perioperative facilities.

Prime-Time Start	Number of Patients	Percent of Patients
Prime Time Start	16810	83.54%
Non-OR Cases	1893	9.41%
Non-Prime Time Start	1420	7.06%
Grand Total	20123	100.00%

Weekend, Holidays, and Prime Time Starts Summary

Row Labels	Number of Patients	Percent of Patients
In-Scope		
Weekday		
Non-Holiday		
Prime Time Start	16175	89.63%
Non-OR Cases	1872	10.37%
Out-of-Scope		
Weekday		
Holiday		
Prime Time Start	37	67.27%
Non-Prime Time Start	18	32.73%
Non-Holiday		
Non-Prime Time Start	1130	100.00%
Weekend		
Non-Holiday		
Prime Time Start	598	67.12%
Non-Prime Time Start	272	30.53%
Non-OR Cases	21	2.36%
Grand Total	20123	100.00%

Simulation Entities Summary

Simulation Entities	Number of Patients	Percent of Patients
In-Scope	18047	**89.68%**
Inpatient	3246	17.99%
NonOR	1872	10.37%
Outpatient	6344	35.15%
SameDayAdmit	5298	29.36%
SDAOther	1287	7.13%
Out-of-Scope	2076	**10.32%**
Inpatient	1697	81.74%
NonOR	21	1.01%
Outpatient	150	7.23%
SameDayAdmit	96	4.62%
SDAOther	112	5.39%
Grand Total	**20123**	

MGH Patient Categories Summary

MGH Patient Categories	Number of Patients	Percent of Patients
AS	5840	29.02%
In-Scope	5744	98.36%
Out-of-Scope	96	1.64%
SD	5631	27.98%
In-Scope	5446	96.71%
Out-of-Scope	185	3.29%
IN	5040	25.05%
In-Scope	3302	65.52%
Out-of-Scope	1738	34.48%
Non-OR	1893	9.41%
In-Scope	1872	98.89%
Out-of-Scope	21	1.11%
RR	1561	7.76%
In-Scope	1530	98.01%
Out-of-Scope	31	1.99%
OB	153	0.76%
In-Scope	149	97.39%
Out-of-Scope	4	2.61%
EE	5	0.02%
In-Scope	4	80.00%
Out-of-Scope	1	20.00%
Grand Total	**20123**	**100.00%**

6.8 Simulation design

6.8.1 Entities

The simulation contains five patient entity types: Outpatients, Inpatients, NonOR, SameDayAdmits, and SDAOther. The entity type instructs the simulation on where to send patients and how to record and summarize the data. Within the OR PRISM database, there are six different patient categories. MGH patient categories are as follows:

- AS- Ambulatory Surgery (Outpatients, at home pre- and post-surgery)
- IN – Inpatient (In the hospital pre- and post-surgery)
- SD- SameDayAdmits (At home pre-surgery, in the hospital post-surgery)
- RR- Outpatients that need a bed after surgery (RPPR)
- OBS – Observation (Uncertain if they will need to stay after surgery and have a hospital bed)
- EE – Mass Eye & Ear (Patients from Mass Eye & Ear, very few of these)

Different sections of each of those categories were split into five simulation entity types:

- Outpatients – Ambulatory Service patient category that went home after surgery (or a nursing home or Spaulding recovery center)
- Inpatients – Inpatient patient category that went to another OR, hospital floor, ICU, or other after surgery
- SameDayAdmits (SDA)– Same Day, RPPR, and Observation patient categories that do not go home or to the ICU after surgery; PACU post-op timestamps were available
- SDAOther – Same Day, RPPR, and Observation that go to the ICU directly after surgery (do not stop at the PACU)

- NonOR – Used peri-op bays but did not go to an OR (Endoscopy, Radiology, Electrotherapy (ECT))

A detailed breakdown of the classification system used is found is Appendix 6.8.

Note that SameDayAdmits that stay overnight in the PACU (PACU departure was the following day after 7:00AM) are classified as SDAOther, so their extremely high wait times[4] are not counted in overall SameDayAdmit wait times.

6.8.2 Locations

The four locations in the system are the Center for Perioperative Care (CPC), Perioperative bays or Post Anesthesia Care Unit (PACU), the Operating Room, and the Hospital Floor. In the CPC patients starting at home before surgery first go to the CPC to be checked in to the hospital, change in to a gown and receive a bed. Before Outpatients can go home, they checkout through the CPC. All patients are routed through the perioperative bays to get prepped for surgery. After surgery they go to the PACU to wake up from anesthesia. The Operating Room is where the surgery is performed. Inpatients start and begin at on the hospital floor or ICU. SameDayAdmits go to hospital floor after being processed in the PACU.

[4] Average wait time of 667 minutes, average PACU length of stay of 1421 minutes

6.8.3 Attributes

Every entity has a list of attributes that is read into the simulation. See Table 39 for a list of these attributes and their descriptions.

Attribute	Description
Entity Type	One of the five entity types
Arrival Time	The number of minutes after 1/1/12 00:00 that the entity arrives to its first process step
CPC_PreOp_LOS	Length of stay (LOS) (in minutes) in the Center for Perioperative Care (CPC)
CPC_PACU_Transport	Amount of time between departing the CPC and arriving in the PACU
PACU_PreOp_LOS	Length of stay (in minutes) in the PACU for pre-operative care
PACU_OR_Transport	Amount of time between departing the PACU and arriving in the OR
OR_LOS	Length of stay (in minutes) in the Operating Room
OR_PACU_Transport	Amount of time between departing the OR and arriving in the PACU
PACU_PostOp_LOS[5]	Length of stay (in minutes) in the PACU for post-operative care
PACU_CPC_Transport	Amount of time between departing the PACU and arriving in the CPC
CPC_PostOp_LOS	Length of stay (in minutes) in the CPC
FormNumber	A unique identification for each patient
Floor	A code that encompasses all the floor restrictions for each patient, matches to a BedNotification (gender, surgery type, and infectious disease)
OperationComplete	A variable that starts as 0 before surgery and increments to 1 once the surgery is complete (see Figure 3)

Table 39: Entity attributes

6.8.4 Arrays

There are two types of arrays that the system keeps record of. The first is NumWaitingRecord. This records the number of patients waiting in the PACU each time a patient leaves or enters the PACU. The second is BedArray. This is an array that starts off with all values at zero. When a BedNotification arrives to the hospital floor it increments the row in the array corresponding to the floor it has availability on by one. When a patient leaves the PACU to go to the hospital floor it decrements the row in the array corresponding to the floor it is going to by one. This is how the system checks to see when a patient can

[5] For Inpatient and Outpatient entities, the PACU Post-op length of stay is defined as PACU arrival time until PACU departure time. However, for SameDayAdmit entities, PACU Post-op length of stay is defined as PACU arrival time until PACU ready to depart time.

leave the PACU and go to the hospital floor (when there is a bed available that meets its specific restrictions).

6.8.5 Processes & Routings

Processes are instructions for all Entity and Location combinations. When Entity X reaches Location Y it follows the instructions to wait for a certain amount of time and once finished, it moves to another location over a designated period of time. Routings are instructions connected to each Entity and Location Process that instructs the entity where to go next, based on certain rules, and what to do through the move (if anything).

See Appendix 6.11 for the specific coding for each process and routing.

6.9 Entity Classification

MedModel Entity Type	Categorization of Patient Categories	# of Patients	Total	*In-Scope*	*Out-of-Scope*	Total
Outpatients	Ambulatory Service patient category that went home after surgery (or a nursing home/Spaulding recovery center)	5491	**6494**	*6344*	*150*	**6494**
	SD/RR/OBS that go home after surgery	880				
	AS patients that do not have PACU timestamps even if the post-op location was a floor	19				
	IN patients that go home after surgery	85				
	IN patients that come through the CPC Pre-op first (go to a floor, have PACU timestamps)	9				
	AS patients that go back through the CPC	9				
	AS that end up in the ICU after surgery	1				
Inpatients	Inpatient patient category that did not go home after surgery (went to another OR, hospital floor, ICU, or other)	4937	**4943**	*3246*	*1697*	**4943**
	Mass Eye & Ear patients	5				
	AS that went to ICU	1				
SameDayAdmits	Same Day, RPPR, and Observation patient categories that do not go home or to the ICU after surgery, PACU post-op timestamps are available	4966	**5394**	*5298*	*96*	**5394**
	AS that went to PACU and then to a floor	319				
	SD/RR/OBS patients that do not go to the CPC pre-op but have PACU timestamps and go to a floor	71				
	SD/RR/OBS patients that go to the PACU and then to a known ICU floor	29				
	IN that come through the CPC and go to a floor afterwards has PACU timestamps	9				
SDAOther	SD/RR/OBS patients that come from home (go through the CPC pre-op) but then go to the ICU directly after surgery (no stop at the PACU)	883	**1399**	*1287*	*112*	**1399**
	SD/RR/OBS that are overnight (PACU departure was the following day after 7am), this is so it will not be counted in wait times	402				
	SD/RR/OBS patients that do not have PACU timestamps (but do come from home and go to a floor)	102				
	SD/RR/OBS patients that go to an OR after the PACU	12				
NonOR	Used peri-op bays but did not go to an OR (Endoscopy, Radiology, Electrotherapy)	1893	**1893**	*1872*	*21*	**1893**
Grand Total				**18047**	**2076**	**20123**

6.10 Floor Numbering System

What SameDayAdmit can use each BedNotification is determined by the floor variable. An array in MedModel is created at the start of each simulation run where all values in the array begin at zero. As a BedNotification arrives to the hospital floor, it increases the row corresponding to the floor number by one. When a SameDayAdmit is ready to depart the PACU it waits until its row in the array corresponding to its floor number is greater than one. As the patient departs the PACU and moves to the hospital floor, the system decrements the floor row in the array by one.

Each of the SameDayAdmits and corresponding BedNotifications are given a floor number based on the floor they went to, their gender, and whether or not they had an infectious disease. All the floors are first numbered individually, however some floors are grouped as the following surgical specialties have multiple floors to which their patients can go.

Surgical Specialty	Grouped Floors
Neurosurgery	Lunder 7 and 8
Orthopedics	White 6 and Ellison 6
Pediatrics	Ellison 17 and Ellison 18
General Surgery, Emergency/Urgency, Oncology	White 7 and Ellison 7

For floors with semi-private rooms (two patients in the same room), BedNotifications need to be gender and infectious disease specific. This constraint was implemented by augmenting the floor number in the following ways:

Constraint	Change in Floor Number
Patient is Male	+100
Patient is Female	+200
Patient has an Infectious Disease	+200

This gives us the following coding system:

Floor Number	Patient Type
0XX	Non-constrained floor
1XX	Male, non-infectious disease
2XX	Female, non-infectious disease
3XX	Male, infectious disease
4XX	Female, infectious disease

Note that for floors with private rooms, the gender and infectious disease constraints are relaxed. These floors are Lunder 6, 6 Neuro ICU, 7, 8, 9, & 10 as well as Philips 20, 21, & 22.

The table below shows all floors, the number of patients going to each floor, and the codes for each possible patient type.

Hospital Floor Location	# of SDAs	Individual Floors	Grouped Floors	M	F	M-InfDisease	F-InfDisease
BIGELOW 11	1	1	1	101	201	301	401
BIGELOW 13	426	2	2	102	202	302	402
BIGELOW 14	302	3	3	103	203	303	403
BIGELOW 6 PICU	1	4	4	104	204	304	404
BIGELOW 7	185	5	5	105	205	305	405
BIGELOW 9 RACU	1	6	6	106	206	306	406
BLAKE 12 NEURO ICU	4	7	7	107	207	307	407
BLAKE 6 TRANSPLANT ICU	2	8	8	108	208	308	408
BLAKE 6 TRANSPLANT ROUTINE	110	9	9	109	209	309	409
CT SCANS	7	10	10	110	210	310	410
DIALYSIS	1	11	11	111	211	311	411
ELLISON 10	8	12	12	112	212	312	412
ELLISON 11	4	13	13	113	213	313	413
ELLISON 13	1	14	14	114	214	314	414
ELLISON 16	6	15	15	115	215	315	415
ELLISON 19	345	18	18	118	218	318	418
ELLISON 4 SICU	8	19	19	119	219	319	419
ELLISON 8	63	22	22	122	222	322	422
INTERVEN. RAD	2	23	23	123	223	323	423

LUNDER 10	4	24	24	24	24	24	24
LUNDER 6	2	*25*	*25*	*25*	*25*	*25*	*25*
LUNDER 6 NEURO ICU	2	*26*	*26*	*26*	*26*	*26*	*26*
LUNDER 9	8	*29*	*29*	*29*	*29*	*29*	*29*
MASS EYE AND EAR	1	30	30	130	230	330	430
OTHER	7	31	31	131	231	331	431
PHILLIPS 20	4	32	32	32	32	32	32
PHILLIPS 21	232	33	33	33	33	33	33
PHILLIPS 22	245	34	34	34	34	34	34
RAD	2	35	35	135	235	335	435
RAD ONC	37	36	36	136	236	336	436
WHITE 11	1	37	37	137	237	337	437
WHITE 8	2	40	40	140	240	340	440
WHITE 9	2	41	41	141	241	341	441
ELLISON 17	70	16	42	142	242	342	442
ELLISON 18	148	17	42	142	242	342	442
ELLISON 6	1078	20	43	143	243	343	443
WHITE 6	713	38	43	143	243	343	443
ELLISON 7	466	21	44	144	244	344	444
WHITE 7	454	39	44	144	244	344	444
LUNDER 7	245	27	45	45	45	45	45
LUNDER 8	194	28	45	45	45	45	45

6.11 Processes & Routings

CPC for ALL entities:

Entity	Location	Operation
ALL	CPC	if OperationComplete=0 then wait CPC_PreOp_LOS if OperationComplete=1 then wait CPC_PostOp_LOS

Output	Destination	Rule	Move Logic
ALL	PACU	IF OperationComplete=0, 1	MOVE FOR CPC_PACU_Transport
ALL	EXIT	IF OperationComplete=1	

PACU for Outpatients, SDAOther, and NonOR entities:

Entity	Location	Operation
Outpatient SDAOther NonOR	PACU	if OperationComplete=0 then wait PACU_PreOp_LOS if OperationComplete=1then wait PACU_PostOp_LOS

Output	Destination	Rule	Move Logic
Outpatient SDAOther or NonOR	CPC	IF OperationComplete=1, 1	MOVE FOR PACU_CPC_Transport
Outpatient SDAOther or NonOR	OperatingRoom	IF OperationComplete=0	MOVE FOR PACU_OR_Transport

PACU for Inpatient entities:

Entity	Location	Operation
Inpatient	PACU	if OperationComplete=0 then wait PACU_PreOp_LOS if OperationComplete=1then wait PACU_PostOp_LOS

Output	Destination	Rule	Move Logic
Inpatient	EXIT	IF OperationComplete=1, 1	
Inpatient	OperatingRoom	IF OperationComplete=0	MOVE FOR PACU_OR_Transport

PACU for SameDayAdmit entities:

Entity	Location	Operation
SameDayAdmit	PACU	if OperationComplete=0 then wait PACU_PreOp_LOS if OperationComplete=1then { PACU_Enter = clock() wait PACU_PostOp_LOS Row=Row+1 NumWaiting=NumWaiting+1 NumWaitingRecord[Row,1]=clock(hr) NumWaitingRecord[Row,2]=NumWaiting LOG "Patient_Time_to_Ready", PACU_Enter Pt_Ready = clock()

```
WAIT UNTIL BedArray[Floor,1]>=1

Row=Row+1
NumWaiting=NumWaiting-1
NumWaitingRecord[Row,1]=clock(hr)
NumWaitingRecord[Row,2]=NumWaiting

}
```

Output	Destination	Rule	Move Logic
SameDayAdmit	HospitalFloor	IF OperationComplete=1, 1	Log "Wait_time", Pt_Ready BedArray[Floor,1]=BedArray[Floor,1]-1
SameDayAdmit	OperatingRoom	IF OperationComplete=0	MOVE FOR PACU_OR_Transport

OperatingRoom for ALL entities:

Entity	Location	Operation
ALL	OperatingRoom	wait OR_LOS OperationComplete=OperationComplete+1

Output	Destination	Rule	Move Logic
ALL	PACU	FIRST 1	MOVE FOR OR_PACU_Transport

HospitalFloor for BedNotification:

Entity	Location	Operation
BedNotification	HospitalFloor	BedArray[Floor,1]=BedArray[Floor,1]+1

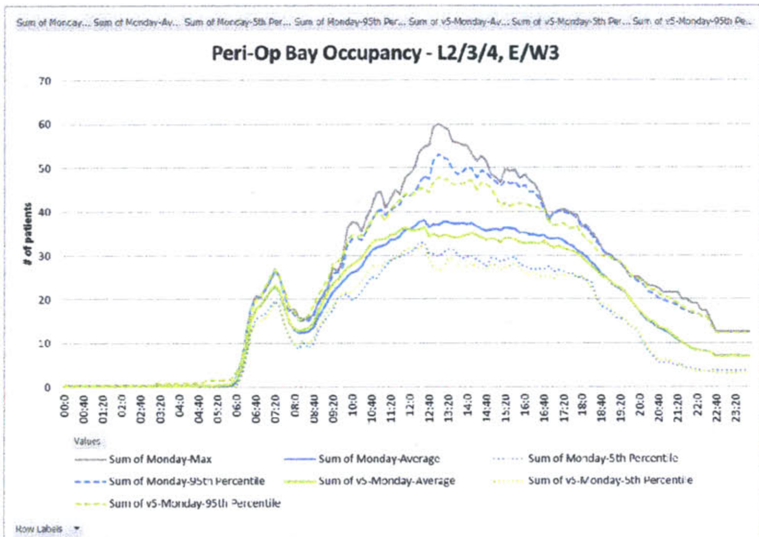
Output	Destination	Rule	Move Logic
BedNotification	EXIT	FIRST 1	

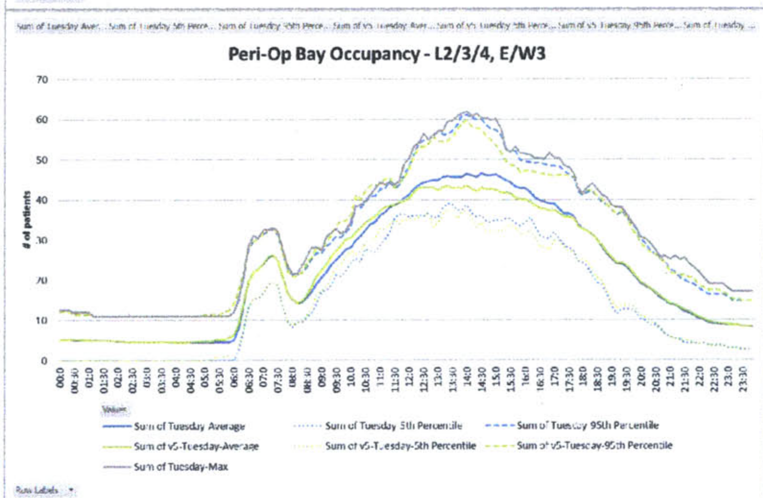
HospitalFloor for SameDayAdmit:

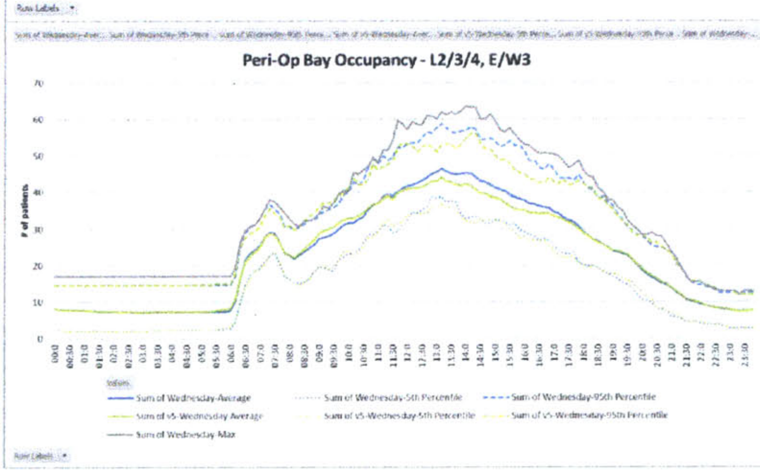
Entity	Location	Operation
SameDayAdmit	HospitalFloor	

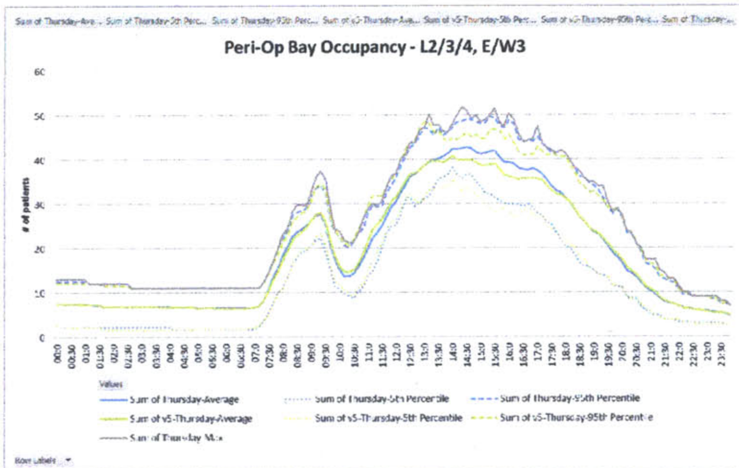
Output	Destination	Rule	Move Logic
SameDayAdmit	EXIT	FIRST 1	

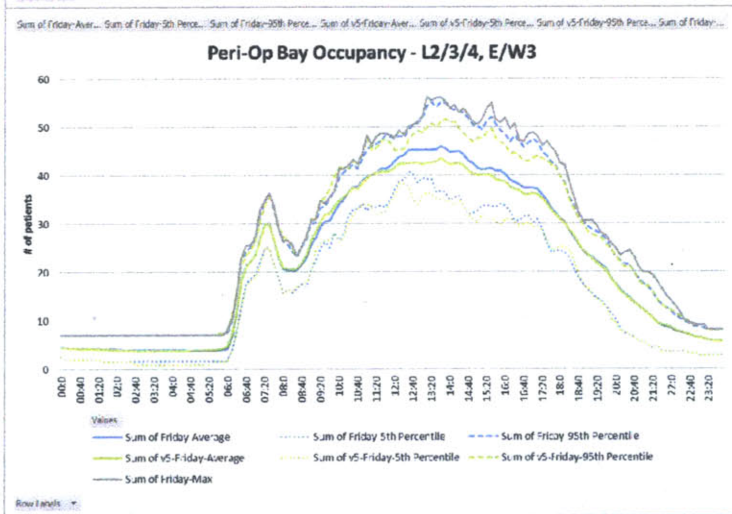
6.12 Peri-Op Bay Occupancy by Day of Week








Peri-Op Bay Occupancy - L2/3/4, E/W3
# of patients
Values
Sum of Thursday-Average
Sum of Thursday-5th Percentile
Sum of Thursday-95th Percentile
Sum of v5-Thursday-Average
Sum of v5-Thursday-5th Percentile
Sum of v5-Thursday-95th Percentile
Sum of Thursday-Max
Row Labels


Peri-Op Bay Occupancy - L2/3/4, E/W3
# of patients
Values
Sum of Friday Average
Sum of Friday 5th Percentile
Sum of Friday 95th Percentile
Sum of v5-Friday-Average
Sum of v5-Friday-5th Percentile
Sum of v5-Friday-95th Percentile
Sum of Friday-Max
Row Labels

7 References

Andrews, P. S. (2012, November 8). *Health Care Reform*. Retrieved 2 27, 2013, from The New York Times: http://topics.nytimes.com/top/news/health/diseasesconditionsandhealthtopics/health_insurance_and_managed_care/health_care_reform/index.html

Etzioni, D., Liu, J., Maggard, M., & Ko, C. (2003). The aging population and its impact on the surgery workforce. *Annals of Surgery, 238*(2), 170–177.

Gigerenzer, G. (2008). Why heuristics work. *Perspectives on Psychological Science, 3*(1), 20-29.

Glauberman, S., & Mintzberg, H. (2001). Managing the care of health and the cure of disease – Part I: Differentiation. *Health Care Management Review, 26*, 56–69.

Health Care Financial Management Association. (2005). *Achieving operating room efficiency through process integration.*

Marcario, A., Vitez, T., Dunn, B., & McDonald, T. (1995). Where are the costs in perioperative care?: Analysis of hospital costs and charges for inpatient surgical care. *Anesthesiology, 83*(6), 1138–1144.

Massachusetts General Hospital. (2012, March). *Hospital Overview - Massachusetts General Hospital.* Retrieved January 15, 2013, from http://www.massgeneral.org/about/overview.aspx

Massachusetts General Hospital. (2012, July). *Massachusetts General Hospital Ranked #1 in the Nation on U.S. News & World Report Honor Roll.* Retrieved January 15, 2013, from http://www.massgeneral.org/about/pressrelease.aspx?id=1483

Price, D. (2011). Managing Variability in Perioperative Process at MGH. Cambridge: Massachusetts Institute of Technology.

ProModel Corporation. (2012, March). Retrieved from MedModel Home - Medical Software - Simulation Software for the Health Care Industry: http://www.promodel.com/products/medmodel/