Prediction and Optimization Techniques to Streamline Surgical Scheduling

by

Ryan M. Graue

B.S. Aerospace Engineering
Saint Louis University, 2008

Submitted to the MIT Sloan School of Management and the Department of Aeronautics and Astronautics in Partial Fulfillment of the Requirements for the Degrees of

Master of Business Administration
and
Master of Science in Aeronautics and Astronautics

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

June 2013

Signature of Author ______________________________
MIT Sloan School of Management, Department of Aeronautics and Astronautics
May 10, 2013

Certified by ______________________________
Vivek Farias, Thesis Supervisor
Robert N. Noyce Career Development Associate Professor, MIT Sloan School of Management

Certified by ______________________________
Deborah Nightingale, Thesis Supervisor
Professor of the Practice, Aeronautics and Astronautics and Engineering Systems Division

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

Accepted by ______________________________
Eytan H. Modiano, Chair, Graduate Program Committee
Professor of Aeronautics and Astronautics

This page intentionally left blank.

Prediction and Optimization Techniques to Streamline Surgical Scheduling

by

Ryan M. Graue

Submitted to the MIT Sloan School of Management and the Department of Aeronautics and Astronautics on May 10, 2013 in Partial Fulfillment of the Requirements for the Degrees of Master of Business Administration and Master of Science in Aeronautics and Astronautics

Abstract

We have created a set of decision support tools to streamline the surgical case scheduling process by allowing surgical wait list cases (elective cases that cannot be assigned a slot on the operating room schedule at the time of booking) to be confirmed onto the operating room schedule up to three weeks in advance of the day of surgery. Prior to our research, wait list cases could not be confirmed more than a few days prior to the desired day of surgery due to uncertainty about available time prior to the release of dedicated OR capacity. Earlier confirmation of wait list cases serves three purposes: (1) to improve patients' ability to plan logistics to prepare for their visits, (2) to reduce wait list case backlogs for surgeons' offices, and (3) to reduce variability in the total daily caseload through proactive decision making. Our contributions assist scheduling personnel in confirming wait list case dates sooner to help medical institutions achieve these benefits. We have developed two Excel-based pieces of software: a prediction tool and a schedule optimization tool. The prediction tool predicts time that is available each day between one and three weeks in advance to accommodate wait list cases, and the schedule optimization tool automates the consolidation process for all cases that are currently booked on a future date so that rooms and equipment are used as efficiently as possible.

Our platform lets users interact with simple GUIs in which they make selections to generate prediction results and optimized daily case schedules. Specifically, our prediction algorithm employs a multiple linear regression model over historical data to forecast unused time, and the optimization tool uses a mixed integer linear program to optimize the daily schedule by consolidating cases into a minimum number of rooms and closing any gaps between cases, subject to constraints that are specific to the facility and the date in question.

We have achieved our desired outcome of maximizing operating room resource utilization by giving human schedulers a set of tools to use on a daily basis that simplifies the scheduling process and confirms wait list cases with more advance notice. This system is generalizable to other areas within healthcare delivery environments and any other industry where tasks are scheduled in advance into a fixed set of resources with a record of historical demand over time.

Thesis Supervisor: Vivek Farias
Title: Robert N. Noyce Career Development Associate Professor, MIT Sloan School of Management

Thesis Supervisor: Deborah Nightingale
Title: Professor of the Practice, Aeronautics and Astronautics and Engineering Systems Division

This page intentionally left blank.

Acknowledgments

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

There are so many people to thank for their advice, encouragement, enthusiasm, and support in relation to this research and my entire academic experience over the last two years. First, the LGO Program office and MIT Sloan Operations Management group have been invaluable both during and prior to my internship engagement in creating the partnership with the host institution, forming a collaborative research environment, and building relationships to set the stage for our workgroup to discover valuable insights. The project would not have been possible without their efforts. Also, the team of individuals with whom I worked at the host institution was instrumental in making the project a success. I would specifically like to thank individuals from Anesthesia, Perioperative Services, OR Scheduling, Department of Surgery, Decision Support, Information Services, and the senior executive team for supporting this work and for dedicating time, effort, and resources to move the project forward. In addition, my thesis advisors, Vivek and Debbie, offered superb advice that shaped the research into a valuable contribution to the healthcare industry. Without their guidance, the results would not have been nearly as relevant and implementable as they are today. I would also like to thank my classmates at MIT and other friends in Boston for helping me work through issues and for making my time here such a fun, rewarding, and unforgettable experience. Finally, I am incredibly grateful for my family, who has continually supported my aspirations, taught me the importance of hard work, and most importantly, reminded me that I can do anything I set out to accomplish. Thank you once again to everyone—without you, I never would have made it to where I am today.

This page intentionally left blank.

Table of Contents

List of Figures

List of Tables

1 Introduction

1.1 Problem Statement and Background

Surgeries and interventional procedures comprise a high-cost, high-impact financial engine for medical institutions. It is widely known that operating rooms (ORs) comprise the largest revenue share (estimated at over 40%) at most hospitals and contribute an equally high proportion of expenses on most hospitals' income statements [8], [22]. Consequently, using OR resources efficiently is critical, particularly as healthcare providers begin to share more financial risk with insurance providers. Unfortunately, unlike transportation businesses and logistics companies that outpace their competition by using analytics to optimize complex processes, even the most technologically advanced medical institutions have not developed similar technology to anticipate fluctuations in surgical demand, maximize OR system revenue, or avoid OR resource conflicts. Instead, the current process for scheduling surgical cases into ORs has been essentially unchanged for over 30 years and is typically performed using human intuition and experience rather than a systematic, consistent process.

The standard OR scheduling process involves dividing the total allocated capacity into a set of fixed blocks. Blocks are time intervals in a particular OR that are assigned to a specific surgeon ("surgeon blocks"), group of surgeons ("group blocks"), or surgical service area ("service blocks"), typically on a weekly basis. In addition, the scheduling process employs a block release system. When blocks are released, any unscheduled block time is made available to other surgeons or services. Most elective surgery blocks release three to five days in advance of the day of surgery. In its current state, the OR scheduling process presents medical institutions with two primary challenges:

1. OR access is quite limited for surgeons without assigned blocks as well as surgeons trying to schedule cases outside of their assigned block time (e.g., wait list cases). The lack of OR access results in many shortcomings:
   - Poor scheduling predictability for surgeons wishing to book non-block cases prior to block release
   - Difficulty planning logistics of surgery for patients due to healthcare providers' inability to confirm non-block cases in advance
   - Potential loss of surgical cases to other medical institutions due to time-based booking restrictions
   - Poor patient satisfaction due to the inability to treat patients in a timely manner
2. The combination of short release times and wide fluctuations in daily surgical demand limits opportunities for dynamic resource allocation and adaptive staff planning, preventing optimal resource utilization and hindering financial results. Specifically, short release times make it difficult to recruit and schedule cases during the window between block release and the day of surgery, resulting in significant amounts of unused OR time. In fact, our research shows that "after the fact" missed opportunity can amount to 30% – 40% of the scheduled daily OR capacity on average, with significant variation from one day to the next. From an operations management perspective, this level of inefficiency clearly represents poor capacity utilization. Moreover, these results will not be sustainable as healthcare providers begin to bear more financial risk under new healthcare reform laws, given that an estimated 32 million Americans will obtain health insurance under the Affordable Care Act while new payment rates are expected to put greater pressure on providers' bottom lines [24].

The primary goals of this research are to increase access to the ORs and to improve perioperative resource utilization and financial performance. At the core, we have developed innovative tools to enhance surgical case scheduling by creating dynamic processes that use case and provider scheduling restrictions and real-time data analysis to drive scheduling decisions.

OR scheduling poses many challenges that are not present in other types of scheduling problems. Besides meeting the restrictions related to block assignments, each case must be scheduled in such a way that all required resources are available throughout the duration of the case. At a minimum, these resources include the surgeon (and in teaching hospitals, a resident), anesthesia team, nursing staff, equipment, and the physical room. If any of these resources is unavailable, the case will be delayed. In addition, the perioperative environment differs from manufacturing in that manufacturing companies can store unsold products in inventory and sell them later, whereas hospitals cannot recover unused OR time. Therefore, healthcare providers need the ability to make proactive decisions to minimize the negative effect of poorly utilized OR resources.

As we will see in Chapter 2, surgical demand fluctuates widely from one day to the next due to a multitude of factors. Of these factors, some are predictable, while others are not. Nevertheless, in designing a dynamic scheduling process to forecast surgical demand and optimize daily OR schedules, it is important that any such system is “smart” enough to drive efficiency regardless of the current market conditions. To meet this need, our proposed dynamic scheduling process demonstrates significant benefits regardless of the surgical demand and total case volume. When demand and OR utilization are high, our dynamic scheduling process allows medical centers to maximize resource utilization by fitting more cases onto the schedule, effectively increasing capacity. On the other hand, when demand and OR utilization are in the low to moderate range, our process identifies available OR time in advance of the day of surgery, markets this available time to surgeons who may have outstanding cases, and attracts new incremental cases to medical institutions.

By automating the use of operational surgical case data to estimate the predictable variability in demand and generate optimal daily OR schedules, our process allows OR managers to make adaptive decisions about modulating staff levels and accommodating future surgical cases further in advance. These adaptive decisions help medical institutions recognize an increase in OR resource utilization and a decrease in costs associated with idle ORs and staff overtime.

1.2 Overview of New Systems

Our suite of adaptive decision support tools facilitates dynamic scheduling, optimizes OR resource utilization, and creates visual displays to aid in performance monitoring. While we will give a detailed description of these tools in subsequent chapters, the following list explains the high-level purpose of each tool.

- **SPORT (System for Predicting OR Time)**

  This tool employs a multiple linear regression model to predict the expected amount of available (unscheduled) OR time on a given date for a set of user-specified services, locations, or blocks. Outputs from SPORT are used to confirm outstanding (non-block) cases in advance or to recruit incremental cases if the predicted surgical demand is less than the total staffed OR capacity.

- **ADOPT (Adaptive Decisions for Optimizing Perioperative Time)**

This tool is based on a mixed integer linear program formulation that gives OR scheduling managers the flexibility to generate a set of optimized schedules with outstanding (non-block) cases added to the set of scheduled block cases. The optimization model can be programmed to trade off several possible objectives (e.g., minimum number of rooms running, maximum surgeon preferences) while conforming to daily scheduling restrictions such as room/case compatibility, surgeon availability, and appropriate staff/case matching. Outputs from ADOPT are used to manage the daily OR schedule and shuffle cases to meet desired objectives.

Each tool is built with a scalable infrastructure so that its benefits can be spread to other specialty areas such as interventional procedure rooms or even to other industries beyond healthcare. In addition, multiple locations within an integrated delivery network can adopt the infrastructure to create an enterprise-wide resource management system.

1.3 Thesis Outline

In Chapter 1, we outlined the importance of using OR resources efficiently, described our research goals, outlined challenges within OR scheduling, and gave an overview of the systems we have developed. Chapter 2 describes OR scheduling in more detail with a discussion of OR scheduling processes, causes of variability in surgical demand, opportunity costs of unused OR time, and a set of standard operational data that can be used to create models to help OR managers make more informed scheduling decisions. We also conduct a literature review on the problem of OR scheduling. Next, we dive into the functionality of our systems, with Chapter 3 dedicated to SPORT and Chapter 4 dedicated to ADOPT. Finally, we conclude in Chapter 5 with a discussion of future work and a summary of the impact of our findings.

2 OR Scheduling: Process, Limitations, and Data Storage

This chapter gives a detailed view into the processes involved in OR scheduling. Specifically, we focus on the block scheduling system, causes and costs of variability in surgical demand, our method of accessing data to create the models that drive SPORT and ADOPT, and a literature review that surveys prior research in OR scheduling.

2.1 Description of the Block Schedule and Release System

Most medical institutions perform OR scheduling with a block system that incorporates predetermined release times. As we mentioned in Chapter 1, blocks are designated time intervals in a particular room (e.g., 7:30 am – 5:00 pm in OR 1) in which a specific surgeon, group of surgeons, or surgical service area is authorized to schedule surgeries. Blocks are "protected" from other surgeons until the point of block release, at which point any unscheduled time is made available for other surgeons to schedule additional cases. For the purposes of our research, we will focus on elective blocks with a four-day release.

From an operations management perspective, one may wonder why hospitals have chosen to use the block scheduling system. Indeed, we have already pointed out that using blocks restricts the schedule by placing constraints on resources, hindering managers' ability to run the ORs at high utilization. Making the full OR schedule available to surgeons on a first-come, first-served basis would increase access for certain surgeons (such as surgeons without block time) and improve managers' ability to monitor future utilization. While some hospitals have been able to eliminate the block scheduling system [38], an open scheduling system is generally not feasible for several reasons:

1. Many surgeons operate clinics or have office hours on certain days of the week and need guaranteed OR time to accommodate their patients each week.

2. Certain ORs need to be left available for urgent and emergent cases that are typically scheduled less than two days in advance.
3. Scheduling similar types of surgeries (e.g., multiple cases for the same surgeon) is most efficient when each case is placed in the same room because doing so maximizes the use of special equipment and specialized staff.

The third observation given above implies that the most efficient blocks are full day blocks because they allow a surgeon or service to utilize a room for the entire day. However, full day blocks are still less efficient than an open scheduling system. Despite the shortcomings associated with block scheduling, we have chosen not to modify the block scheduling system, but instead to create data-driven decision support tools to minimize the losses that result due to the system's inherent inefficiencies.

2.2 Our Focus Area Within the Perioperative Process

As outlined in [31], the perioperative process involves several steps, including case booking, pre-admission testing, schedule consolidation, preoperative assessment, surgery, and post-anesthesia care. Our research focuses on the case booking and schedule consolidation aspects of the process. Elective case bookings typically occur between one week and three months prior to surgery, and schedule consolidation—the human-driven process that involves shuffling cases to maximize resource efficiency—occurs upon block release.

2.3 Variability in Elective Surgical Demand

To be clear, we define elective surgical demand as *the total number of OR minutes scheduled prior to block release* (for the purposes of our research, we do not consider the difference between scheduled case durations and actual case durations). We mentioned in Chapter 1 that elective surgical demand often varies greatly from one day to the next. Figure 1 demonstrates this effect by showing the percentage of unused block minutes available five days prior to the day of surgery (one day prior to block release). The chart represents case booking data for a group of five surgical services over one month of OR days in a suite of 20 ORs at a 650 bed urban academic medical center. From the chart, we see that the amount of open block capacity ranges from approximately 5% – 70% per day over the period, with an average of 42% (depicted by the dashed line). From a manager's perspective, this image demonstrates why staffing at a constant baseline level results in significant scrambling and staff overtime on busy days and excessive idle time (or early dismissal) on slow days. Both of these inefficiencies result in suboptimal cost management. In addition, McManus et al. [26] analyzed intensive care unit (ICU) requests at a large, urban children's hospital and found that variability in scheduled surgical caseloads represents a reducible stress on ICUs, noting that uncontrolled variability limits access to care and weakens a hospital's overall responsiveness to emergencies.

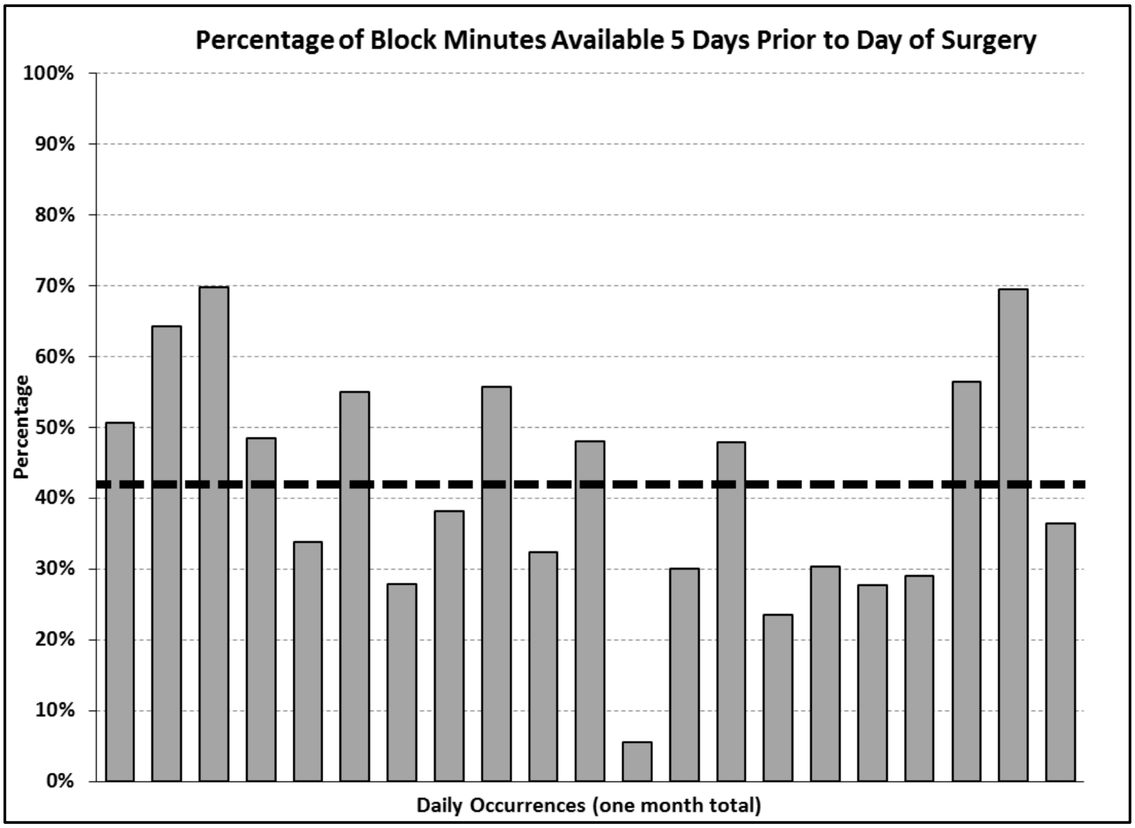


Figure 1. Variation in Available Elective OR Capacity over One Month

The opportunity cost—or missed revenue opportunity—of underutilized OR time is immense. Specifically, at an average underutilization rate of 42%, the total missed revenue opportunity depends on the size of the OR system (hours of block capacity per day) and the system's unit revenue opportunity (average potential reimbursement per OR hour). Table 1 highlights the monthly and annualized missed revenue opportunity for an OR system that does not use 42% of its available block capacity. As shown in the table, the annualized missed revenue opportunity ranges from approximately \$10M for a small system with a low hourly opportunity cost to over \$200M for a large system with a high hourly opportunity cost. These amounts demonstrate the significant economic benefit of operating an efficient OR system.

Table 1. Opportunity Costs of Unused OR Time

Opportunity Cost ($/hr)	Hours of Block Capacity Per Day	Average Hours of Available Block Capacity	Monthly Opportunity Cost	Annual Opportunity Cost
$ 1,000	100	42	$ 882,000	$ 10,584,000
$ 5,000	100	42	$ 4,410,000	$ 52,920,000
$ 10,000	100	42	$ 8,820,000	$ 105,840,000
$ 1,000	150	63	$ 1,323,000	$ 15,876,000
$ 5,000	150	63	$ 6,615,000	$ 79,380,000
$ 10,000	150	63	$ 13,230,000	$ 158,760,000
$ 1,000	200	84	$ 1,764,000	$ 21,168,000
$ 5,000	200	84	$ 8,820,000	$ 105,840,000
$ 10,000	200	84	$ 17,640,000	$ 211,680,000

The question remains, then, as to the causes for the variation in surgical demand. Pandit et al. [29] give a few reasons, including variable referral rates, differences in medical problems for the set of patients having surgery each day, and differences in the amount of time needed to perform the same operation due to co-morbidities and the specifics of each case. Other studies [7], [18] have investigated the effects of relative fees on demand and suggested that physicians have the ability to induce demand, particularly in areas where surgeons are in high supply.

We can categorize the factors that influence elective surgical demand based on their predictability. Table 2 gives examples of predictable and unpredictable factors.

Table 2. Factors that Influence Elective Surgical Demand

PREDICTABLE	UNPREDICTABLE
• Surgical case booking trends • Procedure-specific and surgeon-specific referral rates and cancellation rates • Differences in surgeon fees, facility fees, and insurance reimbursement rates • Seasonality	• Day-to-day case mix • Differences in clinical needs due to co-morbidities • Insurance policy changes • Competitors' strategic decisions

We will now discuss each of the factors listed in Table 2 in more detail.

Predictable Factors

1. Surgical case booking trends

There is natural variability in the timeline required for surgeons book to their cases into the hospital's OR scheduling system. Many factors cause this variability:

1. The rate at which patients seen in clinic decide to have surgery
2. The amount of availability the surgeon has in his or her upcoming blocks
3. The amount of time it takes administrative staff to enter cases into the schedule
4. The amount of available time the surgeon has to work in the OR

However, since the same surgeons generally operate on the same day of the week, there is an opportunity to study booking trends over time for surgeries on the same day of the week to reduce this information flow problem. Specifically, we can predict fluctuations in future demand based on the difference between the current booking trend for a future day of surgery and the past booking trends for the same day of the week.

2. Procedure-specific and surgeon-specific referral rates and cancellation rates

By aggregating and researching historical OR data, we can examine referral rates and cancellation rates by procedure type and by surgeon. With knowledge of referral rates, the nature of upcoming primary care appointments gives OR managers the ability to estimate upcoming demand by predicting how many procedures will be referred to their institution in the future. While changing referral rates do not affect short-term variability directly, they are important because the effects of hospital and physician affiliations and alliances determine long term fluctuations in demand. In addition, with knowledge of procedure-specific and surgeon-specific cancellation rates, statistical analysis can help OR managers anticipate cancellations on future dates based on the types of cases on the schedule and the surgeons that are operating on those dates.

3. Differences in surgeon fees, facility fees, and insurance reimbursement rates

Different health insurance policies dictate varying levels of fees for surgical operations, both for patients (i.e., deductibles and co-pays) and providers. In spite of these differing fee levels (which are often not easy for patients to find), patients typically do not choose their surgeon. Rather, their primary care physicians refer them to a specialist in the appropriate surgical service area. As healthcare reimbursement patterns transition from fee-for-service to fee-for-value, referral patterns (and thus demand) will likely change to reflect the clinical value received in relation to the fees that are charged. Traditionally, referral choices have come from personal relationships between physicians, but more recently, the cost of care as a performance indicator that influences network-wide reimbursement rates under shared risk contracts is becoming an increasing factor in referral generation. Once fee levels are known for different providers and services, the expected changes in demand can be predicted.

4. Seasonality

As one would expect, seasonality contributes to fluctuations in surgical demand. To give two specific examples, OR systems in areas with harsh winter climates often see a surge in orthopedic surgery demand in winter due to an increased number of fractures resulting from icy conditions, and the number of pediatric cases often increases during school vacation weeks. OR managers can make predictions that account for seasonality factors based on past experience.

Unpredictable Factors

1. Day-to-day case mix

Surgeons can predict the number of patients that they will see each day in clinic, but they cannot easily predict how many of those patients will elect to have surgery and what types of procedures they will require. Consequently, these unpredictable factors trickle down and create variability in the OR schedule due to the fluctuating percentage of clinic patients that generate surgery appointments as well as the differences in the amount of OR time that is required for various types of procedures.

2. Differences in clinical needs due to co-morbidities

The same surgical procedure often takes a different amount of time depending on the clinical needs of the patient. Currently, OR managers can predict fluctuation based on the historical performance of the surgeon performing the procedure, but it is more difficult to predict the fluctuation in individual procedure durations because of differences in specific patients' clinical needs. Clinical and demographic data including co-morbidities, age, gender, and other patient-specific criteria may prove useful to sharpen predictions that reflect differences in case length, and thus more accurately reflect true surgical demand.

3. Insurance policy changes

As mentioned, expected changes in demand can be predicted once fee levels for different insurance policies are known. However, the fee changes themselves are an unpredictable factor. Private insurers generally negotiate with providers once every one to three years to establish reimbursement rates, but the changes are difficult to predict in advance.

4. Competitors' strategic decisions

Competing hospitals and surgery clinics may choose to shift their capacity distribution by hiring new surgeons in some services, downsizing other services, or reallocating the amount of OR time that is dedicated to each service. In addition, competitors may increase capacity by building additional ORs from time to time. These actions may be managerial responses to past performance or attempts to brand the organization as a leading provider in a particular surgical service area. Regardless of the reason, other organizations' strategic decisions affect the supply of providers in the market, which in turn affects surgical demand for organizations besides the one making the change. Since external organizations are making these decisions, they are generally unpredictable.

2.4 Data Storage

Much of our research was made possible by the fact that the host institution maintains a repository of OR case data on a SQL server. Database tables on this server provide pertinent information about historical and future cases and blocks, and having direct access to these tables simplifies the design and construction of our automated dynamic scheduling process. Specifically, the host institution records the following information (not an exhaustive list):

Case database table:

- Booking date
- Case date
- Case ID number
- Scheduled duration (and for historical cases, actual duration)
- Scheduled start and end times (and for historical cases, actual start and end times)
- Surgeon
- Surgical service area
- Procedure
- Case location (for scheduled cases, OR in which the case is currently scheduled; for historical cases, OR in which the case was performed)

Block database table:

- Block date
- Block type (surgeon, service, or group)

- Block description
- Block location (specific OR)
- Start time, end time, and total duration
- Surgical service area to which the block belongs

The host institution's database tables update multiple times throughout the day. By accessing these tables through a secure data connection, we employ Microsoft Excel to develop our predictive scheduling and optimization tools. In addition, Excel-based prototypes allow for simple distribution and testing among employees. A major advantage of our design is that in generating predictions and optimal schedules, the code that drives our scheduling tools executes SQL queries to obtain up-to-date information and eliminates the need for the user to perform manual updates or repeatedly download large datasets to perform analyses.

2.5 Literature Review

The literature contains a significant amount of research on the problem of OR scheduling. May et al. [25] outline the area by dividing it into six categories: (1) capacity planning, (2) process reengineering and redesign, (3) the surgical services portfolio, (4) procedure duration estimation, and (5) schedule execution, monitoring, and control. We focus on prior research in process reengineering and redesign and schedule execution, monitoring, and control.

2.5.1 Process Reengineering and Redesign

The surgical scheduling literature related to process reengineering and redesign focuses more heavily on the block time allocation process rather than the process of scheduling individual cases. Blake, Dexter, and Donald [2] used integer programming to develop a block schedule that minimizes the gaps between surgical specialty groups' target amount of block time and the actual amount of block time that the groups are assigned. Blake and Donald [3] showed that using this model at a Toronto hospital resulted in annual savings of approximately $20,000 due to a reduction in schedule development time for OR managers. In [1], Belien, Demeulemeester, and Cardoen developed a decision support system that creates cyclic master surgery schedules using mixed integer optimization to level bed occupancy, concentrate surgeons of the same specialty in the same rooms, and maintain consistent weekly schedules. Gupta and Denton [20] argued that OR time allocation depends on many factors, including operational costs, the demand for certain surgical specialties, and the degree of case urgency and total revenue associated with each specialty group. Similarly, Wachtel and Dexter [35] argued that tactical increases in block time for capacity planning should not be based on a surgeon's or group's OR utilization, but rather on criteria such as contribution margin per OR hour, potential for growth, and the need for limited resources such as ICU beds.

Dexter and Macario [10] described a methodology for changing the allocation of OR time from a system based on historical utilization to a system that maximizes surgical case volume, arguing that many surgical suites do not have a fixed schedule capacity because managers make OR time available for all patients even if cases are scheduled to be completed after the end of the block. Lamiri et al. [23] presented a stochastic model for OR planning that combines Monte Carlo simulation and mixed integer programming to realize gains while considering both elective and emergent surgical demand. Zhang et al. [37] built a methodology for allocating OR capacity to surgical specialties using a finite-horizon mixed integer programming formulation to determine a weekly allocation that minimizes inpatient cost by reducing length of stay.
Taking a different approach, Dexter, Lubarsky, and Blake [9] studied the allocation of resources to surgeons using financial accounting data and used linear programming to determine the mix of surgeons' OR time allocations to maximize contribution margin or minimize variable costs. The

results of [12] showed that OR utilization by itself should not be used to allocate block time to low-volume surgeons.

2.5.2 Schedule Execution, Monitoring, and Control

In regards to schedule execution, monitoring, and control, the literature focuses on statistical analysis used to generate optimal OR schedules. However, as we will see, the metrics that define an optimal OR schedule are varied. Calichman discussed a linear programming model in [4] that allocates capacity to maximize surgical profit, but noted that ensuring optimality in the operational OR schedule depends on surgeons' willingness to adjust existing block schedules. The time series analysis in [13] determined that 12 4-week periods should be used to minimize error in forecasting a surgical group's future elective demand. Charnetski [6] evaluated the cost penalties of idle OR time for early case completions and waiting time for cases following late case completions and used Monte Carlo simulation to provide capacity ranges for effective scheduling that minimize or equalize these two types of costs. In describing a multiple objective surgical case sequencing problem at a freestanding ambulatory surgical center, [5] outlined a weighting strategy that normalizes the objective function (which contains six objectives) and eliminates the need for a human scheduler to set individual weights manually.

Using computer simulation to model OR scheduling, Dexter et al. [15] maximized OR utilization by allocating block time for elective cases based on expected total hours of elective cases, scheduling patients into the first available block if block time is available within four weeks, and otherwise scheduling patients outside of block time. Dexter and Traub [16] investigated scheduling an additional OR case at the earliest start time and the latest start time and concluded that while the earliest start time is more economical and the latest start time performs better in terms of balancing workload, few restrictions need to be placed on patient scheduling to achieve efficient OR time usage.

Dexter et al. [11] outlined a statistical method to maximize labor productivity by decreasing day-to-day variability in underutilized time and found that determining the best day to perform each elective case was much more effective in leveling underutilization than eliminating errors in case durations, turnover time, delays between cases, and daily add-on demand. Realizing the significant financial value of reducing inefficiencies due to the high costs of underutilization and overutilization of OR time, Strum et al. [32] studied cost reduction opportunities rather than pure OR utilization to create an OR capacity planning model. Ogulata and Erol [27] developed a three-stage set of hierarchical multiple criteria mathematical programming models to generate weekly operating room schedules that maximize OR capacity utilization and balance the distribution of operations among surgeon groups in terms of operating days, total operating times, and minimized patient wait times. Epstein and Dexter [17] used statistical power analysis to identify staffing solutions using historical case data and determined that with 30 workdays of data, they could decrease staffing costs by an average of 35% and increase productivity by 27%. Kuo et al. [21] used linear programming to show that an optimized OR allocation could increase weekly professional revenues by 15%.

Velásquez and Melo [33] presented a set packing problem to schedule elective surgeries over a short-term horizon, using column generation and constraint branching to optimize conflicting objectives related to cost management and stakeholder satisfaction. Recognizing that fluctuations in demand require expensive resources to have flexible allocations, Vermeulen et al. [34] presented an efficient patient scheduling approach by enabling resources to be allocated adaptively based on the current and expected demand scenarios. Ozkarahan [28] proposed a goal-programming model that allocates surgeries to ORs based on the needs of the hospital: minimized idle time and overtime, and increased satisfaction of surgeons, patients, and staff. In a similar fashion, Pham and Klinkert [30] proposed a surgical case scheduling approach using a mixed integer linear program based on the multi-mode blocking job shop problem to schedule elective and add-on cases. In [14], computer simulations tested 10 bin-packing algorithms for scheduling add-on elective cases and found that the best fit descending algorithm with fuzzy constraints achieved the best OR utilization.

2.6 Summary

Now that we have outlined the OR scheduling process, discussed the causes and costs of variability in elective surgical demand, described the basic data storage architecture in use at the host institution, and surveyed the literature related to OR scheduling, the next two chapters will transition to descriptions and case studies of the two tools we have developed: SPORT (System for Predicting OR Time), a system that uses a multiple linear regression model to predict OR resource utilization, and ADOPT (Adaptive Decisions for Optimizing Perioperative Time), a system that consolidates the daily OR schedule based on a mixed integer linear program formulation.

3 SPORT: An Approach to Predicting Available OR Time

This chapter gives a detailed analysis of SPORT, a system that predicts available OR time. We begin by outlining the concept of the model and our basic assumptions. Next, we describe the benefits of using the system. We then describe a cross-validation approach that we used to determine the appropriate set of independent variables. Finally, we outline the design of the model, highlight the use of a safety factor to control risk, describe how SPORT is used in practice, and outline a case study based on the use of the system.

3.1 Concept

The underlying assumptions behind SPORT are that for elective surgeries, the vast majority of demand is confirmed prior to block release (in advance of the day of surgery) and administrative practices in use at surgeons' offices are stable. Based on these assumptions, our hypothesis is that historical case booking trends will be an excellent predictor of surgical demand arrival patterns and can thus be used to obtain accurate demand forecasts for future OR dates. These demand forecasts will allow managers to anticipate fluctuations in OR block capacity utilization and make adaptive decisions in advance of the day of surgery. We test our hypothesis on a suite of 20 ORs performing primarily elective, outpatient, and low to moderate acuity inpatient procedures at an urban academic medical center.

3.2 Benefits

To address the shortcomings associated with block scheduling, the ability to forecast future demand provides numerous benefits to all stakeholder groups, as shown in Table 3 below.

Table 3. Benefits of Using SPORT

Surgeon/Office Staff:
• More predictable schedules due to early wait list case confirmations
• Ability to get cases on the schedule during non-block days and times
• Improved patient satisfaction and personal satisfaction due to smoother communication between office and patient (especially for wait list patients)
Patient:
• Ability to plan logistics of surgery (rides and travel plans, child care, time off work) with confidence one to two additional weeks in advance
• Reduced stress due to receiving a confirmed surgery date rather than being placed on a wait list
Hospital Administration, Anesthesia, Nursing Staff:
• More efficient use of OR resources
• Higher staff morale due to more predictable schedules
• Less variation in day-to-day elective surgical caseload
• Ability to plan proactively for daily resource needs instead of reacting on the day of surgery
• Ability for managers to bring on additional staff on high-demand days and/or confirm time off on low-demand days further in advance in a systematic manner, resulting in reduced overtime and idle time costs

3.3 Separating Block Time into Pools

Instead of predicting time for an individual surgeon or service, we group blocks and cases into three pools by identifying surgical services that have comparable resource needs, such as nursing staff and special equipment. Basing predictions on these larger pools of services increases the scope of each prediction and reduces idiosyncratic uncertainties in the prediction results. Blocks and cases are assigned to a pool according to their surgical service. The services for each of the pools are shown in Table 4:

Table 4. Block Time Pools

Pool 1	Pool 2	Pool 3
General Surgery	Orthopedics	Plastic Surgery
OB/GYN	Podiatry	Ophthalmology
Colorectal Surgery		Anesthesiology
Surgical Oncology		Ear, Nose, and Throat
Urology		

Using the database information for cases and blocks, we can determine the following information for any pool at any given point in time:

- $T_{totalblock}$, total block time allotted to the pool
- T_{curr_used}, current number of block minutes used in the pool (sum of all scheduled case durations)
- T_{curr_avail}, current number of block minutes available in the pool (difference between $T_{totalblock}$ and T_{curr_used}).

3.4 Cross-Validation to Determine Proper Regression Model

With the pools in place, our desire is to predict how much block time will be available to accommodate outstanding cases in each pool on future OR dates by employing a multiple linear regression model. In designing the model, we choose independent variables to be snapshots of the total number of minutes booked in each pool at different points in time between the first booking and the time of block release. The dependent variable is the number of minutes booked 5 days prior to surgery because it is the last full day that cases can be booked prior to block release (blocks release <u>at midday</u> 4 days prior to surgery).

Despite knowing the dependent variable, the optimal set of independent variables to choose for the model is unclear. To determine the proper independent variables, we perform cross-validation on a sample data set using 3 sets of independent variables and select the model that results in the highest out-of-sample R^2. In particular, we choose 30 observations corresponding to Pool 1 for 30 consecutive Thursdays and employ "leave-one-out" cross-validation to predict the number of minutes used 5 days prior to the day of surgery from a point in time 10 days prior to the day of surgery. Thus, each validation run uses 29 observations and tests the result on the 30th observation, and the process repeats until all 30 observations have been left out exactly once.

The sample data set used for cross-validation is shown in Table 5.

Table 5. Sample Data for Cross-Validation

10-day prediction						
	Pool 1 (Thurs)	**X1**	**X2**	**X3**	**X4**	**Y**
Obs. #	**Case Start Date**	**-40**	**-30**	**-20**	**-10**	**-5**
1	8/9/12	90	510	900	1365	1785
2	8/16/12	0	0	510	1005	1815
3	8/23/12	480	675	1005	1755	2160
4	8/30/12	0	0	0	375	855
5	9/6/12	0	435	945	1380	1830
6	9/13/12	570	690	1485	2280	2280
7	9/20/12	210	660	660	2400	3210
8	9/27/12	585	750	1410	2475	2655
9	10/4/12	300	495	750	2640	2835
10	10/11/12	480	480	645	1110	2580
11	10/18/12	0	0	555	1470	2370
12	10/25/12	0	360	990	1650	2895
13	11/1/12	375	660	1200	1845	2670
14	11/8/12	0	0	0	885	1290
15	11/15/12	0	90	480	1425	2385
16	11/29/12	0	330	1035	1905	2730
17	12/6/12	330	330	495	1335	1740
18	12/13/12	135	135	135	1440	2580
19	12/20/12	105	435	1020	2025	3030
20	12/27/12	0	75	750	1530	2535
21	1/3/13	75	165	1260	1965	2490
22	1/10/13	0	75	495	615	1065
23	1/17/13	240	435	780	1380	2595
24	1/24/13	105	345	420	1500	2445
25	1/31/13	105	450	450	1275	1680
26	2/7/13	90	90	240	975	1650
27	2/14/13	345	345	630	1890	2790
28	2/21/13	0	0	120	1215	1680
29	2/28/13	405	660	1200	2190	2790
30	3/7/13	345	780	780	780	1950
average						2246

The 3 models we compare use the following sets of independent variables:

- Model 1: Independent variables from 40, 30, 20, and 10 days prior to the day of surgery (X1, X2, X3, and X4 in Table 5)
- Model 2: Independent variables from 30, 20, and 10 days prior to the day of surgery (X2, X3, and X4 in Table 5)
- Model 3: Independent variables from 30 and 20 days prior to the day of surgery (X2 and X3 in Table 5)

A comparison of out-of-sample R^2 values from the cross-validation is shown in Table 6 (refer to Appendix A for the complete set of data tables and results). From this information, we select the formulation represented in Model 2 for our regression. We will explain the details of the modeling approach later in the chapter. In addition, we see that Model 3 results in a very low out-of-sample R^2 as a result of not including the most recent information (10 days prior to the day of surgery), and Model 1 results in overfitting due to including additional information beyond 30 days prior to the day of surgery that does not improve the model.

Table 6. Cross-Validation Results

Model	Out-of-sample R^2
1	0.480
2	0.529
3	0.155

3.5 Designing the Regression

The regression model that SPORT uses builds upon the model presented in [31]. The majority of elective cases are typically booked less than one month in advance, so we design the model to generate predictions for surgery dates between 6 and 15 business days ahead of the current date. For the independent variables, the historical snapshots that we choose change dynamically and depend on the number of days between the current date and the OR date in question, based on the cross-validation results presented above. In addition, the model is designed to include the most up-to-date data available and only considers bookings for the same day of the week as the OR date in question. For example, if the OR date in question is 12 business days ahead of the current date, we only use booking data up to 12 business days prior to the historical surgery dates. However, if the OR date in question is only 6 days ahead, we use booking data up to 6 days prior to the historical surgery dates. The mathematical model can be expressed as follows, where *dt* is the number of days between the current date and the OR date in question, T_{used5} is the number of minutes used 5 days prior to the OR date in question, X_t is the number of minutes booked "t" days prior to the day of surgery, and c_{30}, c_{20}, c_{10}, c_{dt}, and c_5 are regression coefficients.

If $6 \leq dt \leq 10$,

$$T_{used5} = c_{30}X_{30} + c_{20}X_{20} + c_{10}X_{10} + c_{dt}X_{dt} + c_5 \qquad \textbf{Equation 1}$$

If $11 \leq dt \leq 15$,

$$T_{used5} = c_{30}X_{30} + c_{20}X_{20} + c_{dt}X_{dt} + c_5 \qquad \textbf{Equation 2}$$

Given that blocks generally repeat weekly, we use historical booking data (specifically, T_{used5} and the X_t variables in the equations above) from the previous six months to build the regression. Six months of weekly data results in approximately 26 observations and is an ideal size for the model because it provides the following balance:

1. Considers a large enough sample size for statistical relevance
2. Focuses only on the most recent history to reduce seasonality effects and ensure that the pool sizes (amount of total block time allotted) for which the model is being run are likely to be of similar size as those being used to build the model

Table 7 gives an example of the data that are used to generate the regression coefficients (for this example, $dt = 15$).

Table 7. Example of Data Used to Determine Regression Coefficients

Obs. #	X_{30}	X_{20}	X_{15}	T_{used5}
1	180	705	1095	2145
2	555	1395	2190	3090
3	315	1800	1980	2475
4	480	855	1830	2580
5	270	1020	1290	2385
6	75	1290	1770	2835
7	495	855	1275	3000
8	540	1530	2235	3135
9	810	1365	2100	2910
10	180	690	1665	2085
11	510	1425	2355	2895
12	255	720	1440	2055
13	570	1035	1245	2160
14	225	660	1215	2055
15	735	1755	2085	3195
16	195	1035	1320	2250
17	960	960	1350	2550
18	0	165	975	1650
19	0	120	1080	1800
20	450	1005	1155	2160
21	0	825	1140	2295
22	75	690	1110	1905
23	270	855	1125	1830
24	840	975	975	1875
25	660	855	1470	2235
26	255	1200	1995	3090

Once the regression equation is determined, the X_t variables for the desired pool and OR date in question are substituted into Equation 3 or Equation 4 (depending on the value of *dt*) to generate the predictions. Mathematically, we have:

If $6 \leq dt \leq 10$,

$$T_{predused5} = c_{30}X_{30} + c_{20}X_{20} + c_{10}X_{10} + c_{dt}X_{dt} + c_5$$ **Equation 3**

If $11 \leq dt \leq 15$,

$$T_{predused5} = c_{30}X_{30} + c_{20}X_{20} + c_{dt}X_{dt} + c_5$$ **Equation 4**

In Equation 3 and Equation 4, $T_{preduse5}$ is the predicted number of minutes used 5 days prior to the OR date in question, while coefficients c_{30}, c_{20}, c_{10}, c_{dt}, and c_5 are determined from Equation 1 or Equation 2 and the X_t variables are found by accessing case bookings in the database table for scheduled cases.

Knowing $T_{totalblock}$ for the OR date in question, we calculate $T_{predavail5}$, the predicted amount of block time available 5 days prior to the OR date in question, based on the difference between the prediction output, $T_{preduse5}$, and $T_{totalblock}$. If $T_{preduse5}$ is greater than or equal to $T_{totalblock}$, we force $T_{predavail5}$ to zero, and otherwise, $T_{predavail5}$ is the minimum of $T_{totalblock}$ – $T_{preduse5}$ and T_{curr_avail}. In equation form, we have:

$$T_{predavail5} = \begin{cases} 0, & \text{if } T_{predused5} \geqslant T_{totalblock} \\ \min(\mathrm{T_{totalblock} - T_{predused5}, T_{curr\_avail}}), & \text{otherwise.} \end{cases}$$

Equation 5

3.6 Applying a Safety Factor

Values of $T_{predavail5}$ give estimates of available OR time on the day prior to block release for a given pool of blocks, and this information allows OR managers to adjust staffing levels in advance to match predicted resource utilization and recruit outstanding cases depending on the expected case load. However, $T_{predavail5}$ does not give OR managers a sense of the confidence level of the predictions. Since the predictions include error, there is a chance that more block time will be predicted to be available than the amount of block time that is actually available at the moment of block release. To help OR managers minimize the risk of confirming cases beyond the total allotted block capacity, we define and calculate the error standard deviation, or σ_{error}, of each prediction to allow the modeler to make adjustments in risk tolerance. Error standard deviation is calculated as:

$$\sigma_{error} = \sqrt{Var(T_{used5})[1 - R^2_{adj}]}$$

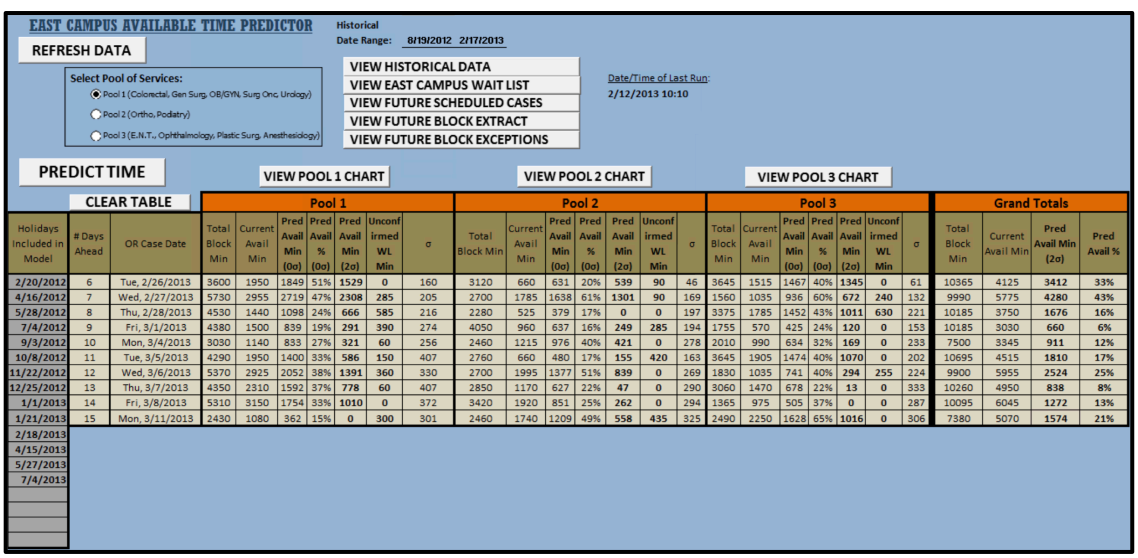
Equation 6

The error standard deviation generates a value, in minutes, that depicts the strength of the prediction (the lower the value, the stronger the prediction). In looking at the terms, σ_{error} increases with $Var(T_{used5})$ and decreases with R_{adj}^2, as one would expect. By subtracting multiples of σ_{error} (safety factors) from $T_{predavail5}$, we can obtain estimates of available OR time with the desired level of risk.

Selecting the proper value of σ_{error} is a strategic decision that carries significant consequences due to an inherent tradeoff. Using low σ_{error} values (0σ or 1σ) increases the risk of overpredicting the amount of available OR time, which may result in overbooking the schedule. On the other hand, using high σ_{error} values (2σ or 3σ) increases the risk of not realizing available OR time, which may result in an avoidable loss of revenue. This tradeoff will be explored further in the case study presented later in the chapter.

3.7 Using SPORT in Practice

To implement the use of SPORT in the OR scheduling process, we employ a graphical user interface in which scheduling managers select pools and run predictions simply by clicking buttons. Figure 2 shows a screenshot of the interface.



Holidays Included in Model	# Days Ahead	OR Case Date	Pool 1: Total Block Min	Current Avail Min	Pred Avail Min (0σ)	Pred Avail % (0σ)	Pred Avail Min (2σ)	Unconfirmed WL Min	σ
2/20/2012	6	Tue, 2/26/2013	3600	1950	1849	51%	1529	0	160
4/16/2012	7	Wed, 2/27/2013	5730	2955	2719	47%	2308	285	205
5/28/2012	8	Thu, 2/28/2013	4530	1440	1098	24%	666	585	216
7/4/2012	9	Fri, 3/1/2013	4380	1500	839	19%	291	390	274
9/3/2012	10	Mon, 3/4/2013	3030	1140	833	27%	321	60	256
10/8/2012	11	Tue, 3/5/2013	4290	1950	1400	33%	586	150	407
11/22/2012	12	Wed, 3/6/2013	5370	2925	2052	38%	1391	360	330
12/25/2012	13	Thu, 3/7/2013	4350	2310	1592	37%	778	60	407
1/1/2013	14	Fri, 3/8/2013	5310	3150	1754	33%	1010	0	372
1/21/2013	15	Mon, 3/11/2013	2430	1080	362	15%	0	300	301
2/18/2013									
4/15/2013									
5/27/2013									
7/4/2013									

OR Case Date	Pool 2: Total Block Min	Current Avail Min	Pred Avail Min (0σ)	Pred Avail % (0σ)	Pred Avail Min (2σ)	Unconfirmed WL Min	σ
Tue, 2/26/2013	3120	660	631	20%	539	90	46
Wed, 2/27/2013	2700	1785	1638	61%	1301	90	169
Thu, 2/28/2013	2280	525	379	17%	0	0	197
Fri, 3/1/2013	4050	960	637	16%	249	285	194
Mon, 3/4/2013	2460	1215	976	40%	421	0	278
Tue, 3/5/2013	2760	660	480	17%	155	420	163
Wed, 3/6/2013	2700	1995	1377	51%	839	0	269
Thu, 3/7/2013	2850	1170	627	22%	47	0	290
Fri, 3/8/2013	3420	1920	851	25%	262	0	294
Mon, 3/11/2013	2460	1740	1209	49%	558	435	325

OR Case Date	Pool 3: Total Block Min	Current Avail Min	Pred Avail Min (0σ)	Pred Avail % (0σ)	Pred Avail Min (2σ)	Unconfirmed WL Min	σ
Tue, 2/26/2013	3645	1515	1467	40%	1345	0	61
Wed, 2/27/2013	1560	1035	936	60%	672	240	132
Thu, 2/28/2013	3375	1785	1452	43%	1011	630	221
Fri, 3/1/2013	1755	570	425	24%	120	0	153
Mon, 3/4/2013	2010	990	634	32%	169	0	233
Tue, 3/5/2013	3645	1905	1474	40%	1070	0	202
Wed, 3/6/2013	1830	1035	741	40%	294	255	224
Thu, 3/7/2013	3060	1470	678	22%	13	0	333
Fri, 3/8/2013	1365	975	505	37%	0	0	287
Mon, 3/11/2013	2490	2250	1628	65%	1016	0	306

OR Case Date	Grand Totals: Total Block Min	Current Avail Min	Pred Avail Min (2σ)	Pred Avail %
Tue, 2/26/2013	10365	4125	3412	33%
Wed, 2/27/2013	9990	5775	4280	43%
Thu, 2/28/2013	10185	3750	1676	16%
Fri, 3/1/2013	10185	3030	660	6%
Mon, 3/4/2013	7500	3345	911	12%
Tue, 3/5/2013	10695	4515	1810	17%
Wed, 3/6/2013	9900	5955	2524	25%
Thu, 3/7/2013	10260	4950	838	8%
Fri, 3/8/2013	10095	6045	1272	13%
Mon, 3/11/2013	7380	5070	1574	21%

Figure 2. SPORT Interface

In addition, within SPORT, users can choose to view charts for each pool that show graphical depictions of $T_{totalblock}$, T_{curr_avail}, and $T_{predavail5}$ with safety factors ranging from 0σ to 3σ for each date between 6 and 15 business days ahead (see example in Figure 3 below). These charts update dynamically and are used as decision support tools to achieve the desired benefits of confirming outstanding non-block cases in advance and matching staffing levels to predicted demand in advance of the day of surgery. To confirm outstanding non-block cases, OR managers can quickly determine high-availability days on the chart and match this availability with outstanding cases for those dates.

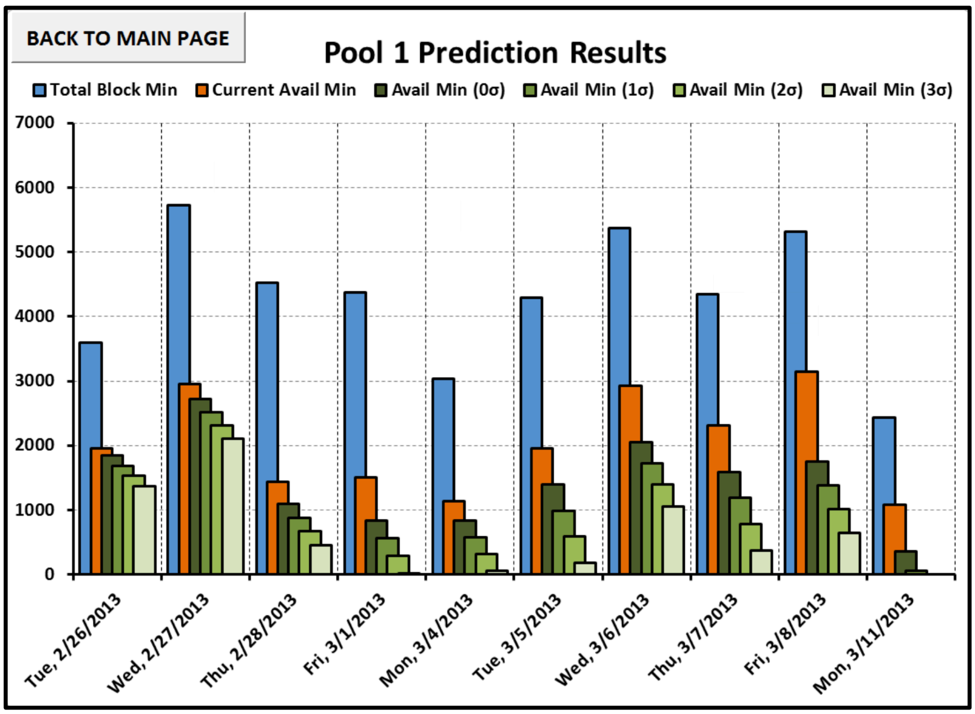


Figure 3. Example of Prediction Results

We will now study an example of how OR managers can read and use the information SPORT provides. In Figure 3, for each OR date, the blue columns represent the total number of block minutes allotted to Pool 1 and the orange bars depict the number of block minutes that are currently available (at the time of the prediction). The green bars depict the number of block minutes predicted to be available 5 days prior to block release with different safety factors (lighter shades correspond to more conservative predictions). In looking at the chart, we see that for 2/27/2013, even the most conservative prediction (3σ) shows that over 2000 minutes are expected to be available. With this information, OR managers can refer back to the interface to compare outstanding wait list cases to high-availability days such as 2/27/2013. Figure 4 (a zoomed-in subset of Figure 2) shows an example of tabulated prediction results corresponding to the bar chart shown in Figure 3, and looking at this table, the OR manager sees 285 unconfirmed (outstanding) wait list minutes for 2/27/2013 (referring to the second to last column in Figure 4). Noting the large gap between the total duration of the outstanding wait list cases (285 minutes) and the OR time that is predicted to be available on that day at the desired level of risk (2308 minutes at 2σ for this example), the OR manager can discover an opportunity to confirm those cases in advance of block release.

OR Case Date	Total Block Min	Current Avail Min	Pred Avail Min (0σ)	Pred Avail % (0σ)	Pred Avail Min (2σ)	Unconfirmed WL Min	σ
Tue, 2/26/2013	3600	1950	1849	51%	**1529**	**0**	160
Wed, 2/27/2013	5730	2955	2719	47%	**2308**	**285**	205
Thu, 2/28/2013	4530	1440	1098	24%	**666**	**585**	216
Fri, 3/1/2013	4380	1500	839	19%	**291**	**390**	274
Mon, 3/4/2013	3030	1140	833	27%	**321**	**60**	256
Tue, 3/5/2013	4290	1950	1400	33%	**586**	**150**	407
Wed, 3/6/2013	5370	2925	2052	38%	**1391**	**360**	330
Thu, 3/7/2013	4350	2310	1592	37%	**778**	**60**	407
Fri, 3/8/2013	5310	3150	1754	33%	**1010**	**0**	372
Mon, 3/11/2013	2430	1080	362	15%	**0**	**300**	301

Figure 4. Example of Tabular Prediction Results

3.8 Case Study: Pilot Testing SPORT

As we mentioned, choosing the appropriate safety factor is an important decision in implementing SPORT. The ultimate goal is twofold: to maximize ease of OR access for all surgeons and to prevent prediction errors that may lead to an overbooked schedule. Unfortunately, these objectives are in conflict, and as we will see in detail in the following case study, there are risks involved with focusing on either objective independently.

Let's assume for the moment that an institution simply wants to maximize ease of access, in which case OR managers may choose to employ SPORT using no safety factor (0σ). Without a safety factor, the predictions will show a large amount of OR time available (compared to predictions at higher safety factors) and as a result, surgeons will have an easier time confirming outstanding cases in advance. However, under this level of risk, the elective schedule is expected to populate very quickly. As a result, there is minimal protection against overbooking the schedule, particularly in the event of unpredictable, nonstandard booking behavior, such as a group of surgeons in the same pool booking an extreme number of cases immediately prior to block release. Overbooking the OR schedule is an undesirable outcome because if it were to happen, some cases may have to get cancelled or delayed until late in the evening, decreasing the quality of care that patients receive and leading to increased overtime hours and lower morale for surgical support staff.

Alternatively, if another institution wants to guarantee that overbooking never occurs, its OR managers may choose to employ SPORT using a conservative safety factor (3σ). In this case, it is extremely unlikely that overbooking will occur; however, access will be greatly hindered by the fact that the predictions will show much less available OR time than at lower safety factors. With more restricted OR access for surgeons, the institution will be unable to accommodate additional cases in any available OR time that goes unidentified. These missed opportunities create frustration for surgeons and patients and result in suboptimal financial outcomes by preventing outstanding cases from entering the OR schedule and generating incremental revenue.

In light of these competing objectives, we performed a two-month pilot test at the host institution during July and August 2012 to analyze the consequences of applying differing levels of risk to the predictions. During the pilot test, we simulated the use of SPORT by calculating and recording predictions for Pool 1 (General Surgery, OB/GYN, Colorectal Surgery, Surgical Oncology, and Urology) and Pool 2 (Orthopedics and Podiatry) using safety factors of 0σ, 1σ, 2σ, and 3σ. Then, on the day prior to block release (5 days prior to the day of surgery), we determined the actual number of OR minutes available and compared this value with the predictions from 6, 10, and 15 OR days in advance. The results are shown in Table 8, Table 9, Table 10, and Table 11.

Over the two-month period, 44 OR days were analyzed in total. For the 6, 10, and 15 OR day advance predictions, we report the number of missed opportunity occurrences and overprediction occurrences, total predicted availability, total and average missed opportunity, and total and average overprediction (with overpredictions being depicted as negative values). We will use the Pool 1 example (Table 8 and Table 9) to discuss our results.

In Table 8, we see that as the safety factor increases, the number of missed opportunity occurrences increases, along with the total amount of missed opportunity and the average missed opportunity. On the other hand, the total predicted availability decreases as safety factor increases. These trends represent the inherent tradeoff: as we reduce the risk of overpredicting availability, we leave more opportunity unrealized. The variation between 0σ and 3σ is drastic—we see that in some instances, the total predicted availability at 3σ over the period is only 40% – 75% of the predicted availability at 0σ, demonstrating that increasing the safety factor from 0σ to 3σ results in having a significant amount of available OR time left unrealized.

On the other hand, Table 9 shows overprediction results. We see trends that are the opposite of those in Table 8. Specifically, as the safety factor increases, the number of overprediction occurrences decreases, along with the total amount of overprediction and the average overprediction. In particular, we see that there are very few occurrences of overprediction for 2σ and 3σ predictions. In addition, the magnitudes of total overprediction are much less than those of total missed opportunity. The overprediction results are somewhat misleading, however, because they do not represent a guaranteed OR overbooking event. Instead, they simply show that the model predicted more availability than the actual amount of time that was available upon block release. OR managers would have to book additional cases up to the prediction amount (beyond the actual availability) during an overprediction occurrence in order for a true overbooking event to occur in these scenarios.

Table 8. Missed Opportunity Summary (Pool 1)

		Safety Factor			
Days Ahead		**0σ**	**1σ**	**2σ**	**3σ**
6	Missed opportunity occurrences	26	35	40	42
6	Total predicted availability (min)	84000	77633	71349	65065
6	Total missed opportunity (min)	3276	7836	13240	19124
6	Average missed opportunity (min)	126	224	331	455
10	Missed opportunity occurrences	31	38	41	43
10	Total predicted availability (min)	80183	68186	56355	44703
10	Total missed opportunity (min)	9631	19148	29570	40921
10	Average missed opportunity (min)	311	504	721	952
15	Missed opportunity occurrences	33	40	43	44
15	Total predicted availability (min)	75990	59687	44031	29293
15	Total missed opportunity (min)	14295	27503	42036	56597
15	Average missed opportunity (min)	433	688	978	1286

Table 9. Overprediction Summary (Pool 1)

		Safety Factor			
Days Ahead		**0σ**	**1σ**	**2σ**	**3σ**
6	Overprediction occurrences	18	9	4	2
6	Total predicted availability (min)	84000	77633	71349	65065
6	Total overprediction (min)	-3212	-1406	-528	-129
6	Average overprediction (min)	-178	-156	-132	-65
10	Overprediction occurrences	13	6	3	1
10	Total predicted availability (min)	80183	68186	56355	44703
10	Total overprediction (min)	-4554	-2074	-665	-364
10	Average overprediction (min)	-350	-346	-222	-364
15	Overprediction occurrences	11	4	1	0
15	Total predicted availability (min)	75990	59687	44031	29293
15	Total overprediction (min)	-4395	-1300	-176	0
15	Average overprediction (min)	-400	-325	-176	0

Table 10. Missed Opportunity Summary (Pool 2)

		Safety Factor			
Days Ahead		**0σ**	**1σ**	**2σ**	**3σ**
6	Missed opportunity occurrences	29	33	41	42
6	Total predicted availability (min)	50170	46137	42161	38185
6	Total missed opportunity (min)	2422	5325	8769	12531
6	Average missed opportunity (min)	84	161	214	298
10	Missed opportunity occurrences	23	33	39	44
10	Total predicted availability (min)	50113	41444	33056	25110
10	Total missed opportunity (min)	5411	10765	17823	25395
10	Average missed opportunity (min)	235	326	457	577
15	Missed opportunity occurrences	26	36	42	44
15	Total predicted availability (min)	48171	34776	22874	12765
15	Total missed opportunity (min)	8068	17575	27710	37740
15	Average missed opportunity (min)	310	488	660	858

Table 11. Overprediction Summary (Pool 2)

		Safety Factor			
Days Ahead		**0σ**	**1σ**	**2σ**	**3σ**
6	Overprediction occurrences	15	11	3	2
6	Total predicted availability (min)	50170	46137	42161	38185
6	Total overprediction (min)	-2087	-956	-424	-211
6	Average overprediction (min)	-139	-87	-141	-105
10	Overprediction occurrences	21	11	5	0
10	Total predicted availability (min)	50113	41444	33056	25110
10	Total overprediction (min)	-5019	-1704	-374	0
10	Average overprediction (min)	-239	-155	-75	0
15	Overprediction occurrences	18	8	2	0
15	Total predicted availability (min)	48171	34776	22874	12765
15	Total overprediction (min)	-5734	-1846	-79	0
15	Average overprediction (min)	-319	-231	-39	0

Figure 5 and Figure 6 show graphically the tradeoff between missed opportunity and overprediction over the two-month period, using predictions from 10 OR days in advance. These figures give a visualization of the relative scale of missed opportunity versus overprediction for different safety factors. As OR managers implement SPORT into their scheduling processes, they will need to select an appropriate safety factor that effectively balances the risk of overpredicting availability against the risk of missing the opportunity to book cases into available OR time.

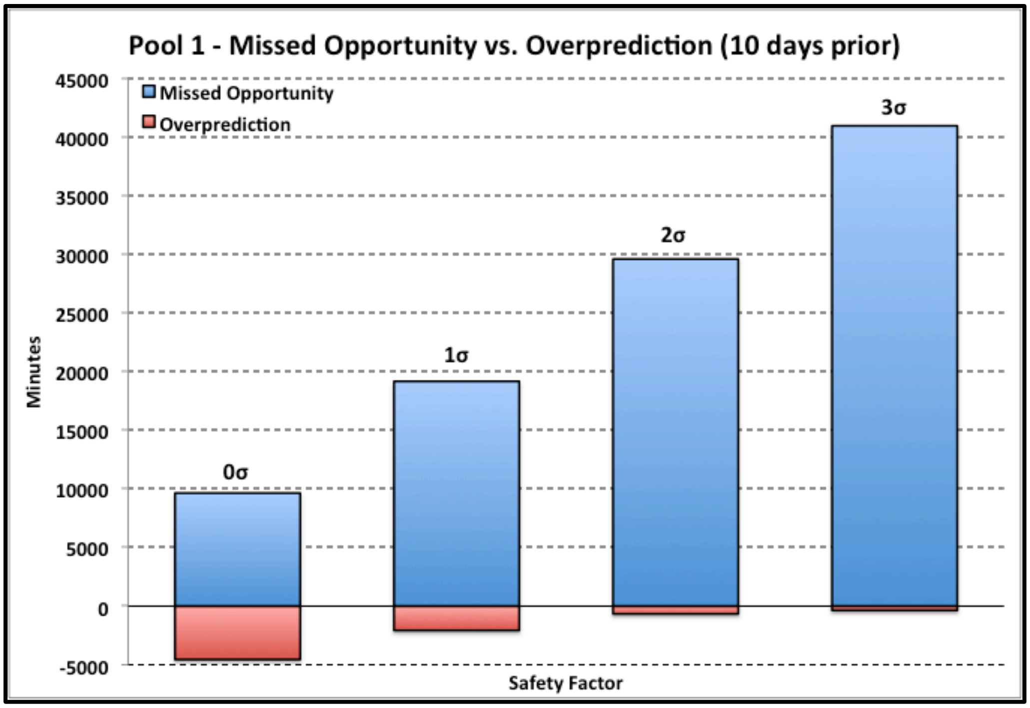


Figure 5. Missed Opportunity vs. Overprediction (Pool 1)

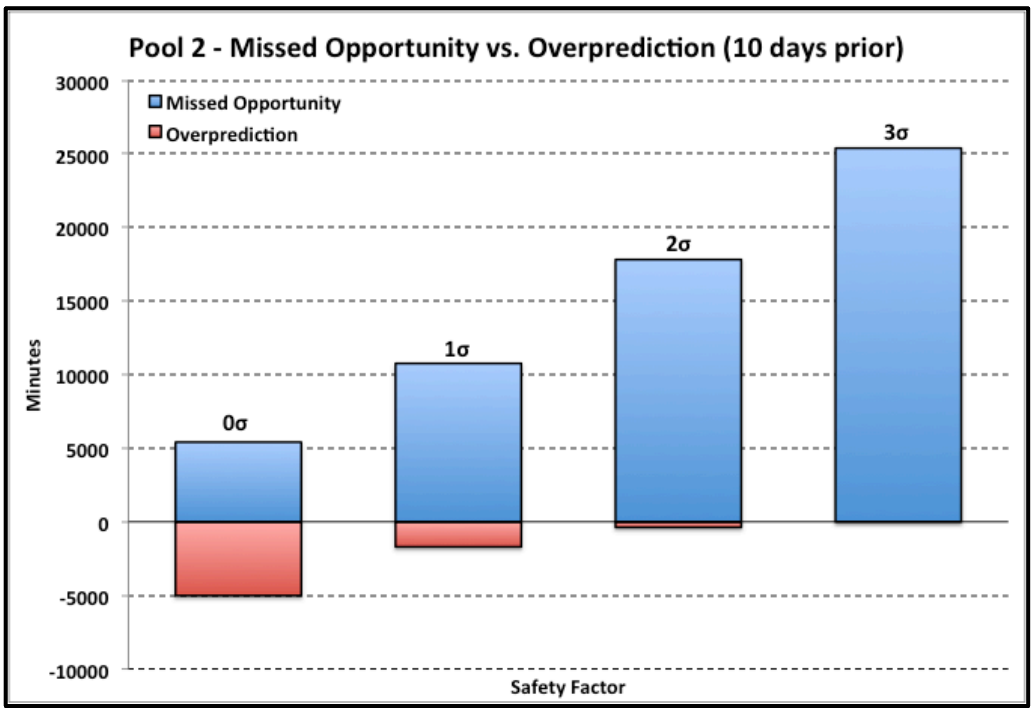


Figure 6. Missed Opportunity vs. Overprediction (Pool 2)

In both pools, we see that for 10 OR days prior to the day of surgery, at a safety factor of 0σ, missed opportunity and overprediction are relatively similar, whereas at higher safety factors, the missed opportunity skyrockets and the overpredictions nearly disappear. In fact, between these two pools, using a safety factor of 3σ results in over 65,000 minutes of missed opportunity, which corresponds to 114 room-days of unrealized availability over the pilot test period (based on an OR schedule of 7:30 am – 5:00 pm).

Relating back to our hypothesis, we proposed that by using operational surgical case data to estimate variability in demand, we would be able to make adaptive decisions about modulating staff levels and accommodating outstanding cases further in advance, resulting in an increase in OR resource utilization and a decrease in costs associated with idle ORs and staff overtime. The pilot test results support our hypothesis, as the predictions serve as helpful decision support tools that accurately forecast future surgical demand arrival patterns. SPORT's predictions help OR managers confidently make operational decisions to recognize the benefits we have outlined, while also showing them the tradeoffs associated with choosing different safety factors.

4 ADOPT: An Approach to Optimizing the Daily OR Schedule

This chapter describes ADOPT, a mixed integer linear program that optimizes the daily OR schedule. We begin with a description of the managerial challenges related to optimizing the OR schedule and then discuss the benefits of the model. Next, we outline the model formulation, discuss the details and performance characteristics of the model, and describe our prototype. We conclude the chapter with a case study that depicts a specific example of the optimization results and a discussion of how ADOPT improves the current OR schedule optimization process.

4.1 Managerial Challenge

Despite the benefits of predicting surgical demand, another major operational challenge for healthcare executives and OR managers remains largely unsolved—OR schedule optimization. OR scheduling managers refer to schedule optimization in many ways, including "room consolidation," "opening and closing rooms," and "finalizing the elective schedule." The challenge lies in the fact that once the elective block schedule releases, cases on the OR schedule must be adjusted so that rooms, staff, and equipment are used as efficiently as possible. However, the objective in optimizing the daily OR schedule is not entirely clear. In particular, there are many factors that an OR scheduling manager must consider, such as rooms running, surgeon preferences, schedule disruption, and room compatibility. We will describe each of these factors briefly:

- Rooms running – The total number of ORs in which at least one case occurs on a particular day. OR scheduling managers aim to minimize rooms running to utilize staff efficiently.

- Surgeon preferences – The specific ORs and times of day in which a surgeon prefers to operate. OR scheduling managers want to adhere to as many surgeon preferences as possible so the surgeons continue to bring their cases to the institution.
- Schedule disruption – A measure of the number of cases that get moved to different rooms or time slots during schedule optimization. OR scheduling managers try to minimize schedule disruption to reduce the burden for surgeons, staff, and patients.
- Room compatibility – A measure of how compatible the room assignments are for the set of cases to be performed (some rooms are not well suited for certain types of cases). OR scheduling managers want to maximize room compatibility to ensure superior quality of care and to give surgeons and staff the best possible environment to perform surgery.

It is unrealistic to expect a human being to optimize each of these factors simultaneously, and yet this is what OR scheduling managers are expected to do every day. Adding to the OR scheduling challenge is the fact that these individuals are expected to remember all of the criteria for each of the factors and apply those criteria when finalizing the schedule. ADOPT is a tool that reduces the mental capacity required to optimize the OR schedule by capturing many of these criteria and generating daily OR schedules systematically.

In practice, the process of optimizing the daily OR schedule is also subject to many clinical and resource-related constraints as well as political struggles. These difficulties create tension between surgeons (who are typically not employed by the hospital and are primarily interested in having access to the ORs to perform their cases while managing their office and clinic schedules to accommodate patients) and hospital administrators (who wish to run the OR schedule efficiently to maximize financial performance and keep employee morale high). Unfortunately, hospitals typically do not have a system that evaluates these tradeoffs quantitatively. Instead, as we just described, an individual clinical OR scheduling manager or team of OR leaders must navigate constraints each day and manually shift cases one-by-one to strike a balance between surgeon satisfaction and efficient schedule operation. This process is seemingly difficult to systematize because each day provides new problems and constraints that are difficult for human beings to resolve in a way that provides an optimal solution.

Without an automated schedule optimization system, OR scheduling managers typically shift cases to consolidate the daily OR schedule into the fewest number of active rooms that are required to accommodate all cases for the day (i.e., minimize rooms running). As we briefly mentioned, the key driver of room consolidation is to optimize staffing. Nursing and anesthesia staff members are typically assigned to a particular OR for the entire day, regardless of how many cases are booked into the room. As a simple example, for a set of 10 ORs with each one running an 8-hour block, we would have 80 hours of available capacity. If only 64 hours of cases were booked at the time of block release, clinical managers and hospital administrators would prefer to consolidate the cases to run 8 rooms at full capacity so they could staff 2 fewer rooms and eliminate the corresponding idle labor costs. At the host institution, on average, approximately 2.5 nurses are required to staff an OR for 8 hours. Based on this requirement, for the single-day example we outlined above, the host institution can save the idle labor cost of 40 hours of nursing time (5 nursing FTEs) by consolidating the OR schedule and closing 2 rooms. Most importantly, optimizing the schedule to reduce idle labor costs does not require that medical institutions reduce staff count; rather, it gives OR managers prospective knowledge to flex staff hours across days to match staffing levels to patient demand on a daily basis. Specifically, in this example, nursing staff that give up hours due to schedule consolidation can return on a high demand day later in the week to make up their standard hours while lowering the overtime expense for the organization.

To address the challenges described thus far in Chapter 4, we have developed ADOPT, an automated mixed integer linear program that shifts cases and determines optimal daily OR schedules that strike a balance among the set of competing objectives we have described. In the next section, we will discuss the benefits of the system.

4.2 Benefits

The benefits of an automated daily OR schedule optimization system are many:

1. Ability to evaluate schedules that meet differing objectives. The most straightforward benefit of a mathematically driven schedule optimization system is the ability to view distinct schedule solutions that trade off objectives. For example, users of ADOPT can decide how much weight to place on potentially conflicting schedule factors such as total rooms running, surgeon satisfaction, and case start time displacement, and quickly review the optimal schedule under different weighting scenarios to understand the interrelationships between these factors.
2. Ability to change behavior and address political barriers. Surgeons typically do not like their cases to be moved once they are booked, particularly if the move involves giving up the first case of the day in a particular room (since doing so reduces the level of control they have over their personal schedules and increases the risk of being delayed). At the same time, OR managers often struggle to demonstrate to surgeons the purpose of consolidating the schedule while relying solely on empirical reasoning. A proven, data-driven consolidation approach creates a tangible starting point for discussing the system-wide benefits of shuffling cases and also demonstrates the entire set of moves across the

system rather than strictly those that belong to the surgeon with whom the conversation is being held.

3. <u>Ability to spend less time modifying the OR schedule manually</u>. As mentioned above, manually modifying the schedule is an arduous process that is time consuming, stressful, and challenging—and must be repeated every day. With an automated schedule optimization system, managers that control the OR schedule can spend less time manually modifying the schedule and use the tool to view several different options before choosing to make one operational. This process reduces the amount of time needed to confirm schedule modifications and allows OR managers to focus more on clinical duties and expanding their planning horizon to dates further into the future.
4. <u>Ability to determine a schedule that maximizes expected revenue or expected contribution margin</u>. While we will not present a formulation in this thesis that focuses on financial results, ADOPT could incorporate financial data (such as expected contribution per OR hour for each procedure type) to determine schedules that optimize the expected financial performance of the OR system. A schedule optimization system that considers financial characteristics will be especially critical in the years ahead as healthcare reform policies will place a heavier financial burden on hospitals by shifting from a fee-for-service reimbursement model to a revenue model based on global payments. In the new healthcare environment, maximizing throughput will no longer necessarily result in the best financial outcomes, so hospitals will benefit from a system that accounts for financial implications when evaluating OR scheduling decisions. However, one limitation of such a model is that the disparity in reimbursement rates and profitability among different procedure types may result in optimal solutions that suggest

an unreasonable case mix—potentially eliminating some procedure types from the OR schedule entirely. These solutions may not always be feasible depending on the mission of the institution and the market demand for the most profitable procedures; nevertheless, a scheduling system based on profitability would still help healthcare executives better understand how to optimize their OR suite's financial results. To avoid some of the infeasible solutions that may eliminate low-margin cases, ADOPT could include case mix constraints that maintain volume above a specified threshold for each surgical service or procedure type.

4.3 Model Formulation

Now that we have addressed the managerial challenges related to OR scheduling and outlined the benefits of ADOPT, we will discuss the formulation of the optimization model. For our formulation, we use increments of 15 minutes because the host institution breaks its OR time into 15 minute slots. However, the model can be extended to suit other organizations that use different scheduling increments.

To start, we will define subscripts for the formulation criteria and decision variables as follows:

Subscript i: Cases
Subscript r: Rooms
Subscript j: Products (time intervals in a particular Room)
Subscript t: Resources (15 minute time slots independent of Room)

We define the following formulation criteria (with qualitative descriptions below):

$X_{ij} = 1$ if Case i is assigned to Product j prior to optimization; 0 otherwise
$M_{ij} = 1$ if Case i is compatible with Product j; 0 otherwise
$X_{rt} = 1$ if Resource t in Room r contains a case; 0 otherwise
C_{ij} denotes the utility "cost" of assigning Case i to Product j ($0 \leqslant C_{ij} \leqslant 1$)
S_j denotes the start time of Product j
S_i denotes the start time of Case i prior to optimization
S'_i denotes the start time of Case i after optimization

X_{ij}: Entries are populated uniquely prior to running the model using the case schedule for the OR date.

M_{ij}: Entries are determined through conversations with clinical staff to determine which types of cases can be performed in which rooms. In addition, some M_{ij} entries can be set to zero if surgeons only have partial availability on a certain day.

X_{rt}: Entries change as the model is being run and are used as constraints to restrict overlapping of cases (i.e., more than one case using the same Resource in a particular Room).

C_{ij}: Entries are subjective determinations of operational utility cost (not monetary cost) that are determined from criteria such as surgeon preferences, location of required materials, and the degree of room/case compatibility. C_{ij} values range from 0 to 1, where 0 represents maximum utility cost and 1 represents minimum utility cost.

Decision variables are defined as follows:

$X'_{ij} = 1$ if Case i is assigned to Product j; 0 otherwise
$P_i = 1$ if Case i is assigned to phantom* room; 0 otherwise
$Y_r = 1$ if Room r has at least one case; 0 otherwise
$T_i = |S_i - S'_i|$

*imaginary room in which wait list cases exist prior to optimization

The objective function aims to determine the optimal solution with respect to five factors:

1. Number of rooms running (ORs with at least one case)
2. Sum of absolute values of start time differentials (differences in start time if model shifts cases earlier or later in the day)
3. Number of cases unchanged (cases that do not change time or room after running the model)
4. Total utility cost of case assignments (relative utility gained from operating the schedule using a particular set of room/case combinations)

5. Number of wait list cases accommodated (confirmed onto the OR schedule)

The model

$$\min\ K_1 \sum_r Y_r + K_2 \sum_i T_i - K_3 \sum_{i,j} X_{ij} X'_{i,j} + K_4 \sum_{i,j} C_{ij} X'_{i,j} + K_5 \sum_i P_i$$

$$\begin{aligned}
&s.t.\\
&\textstyle\sum_j M_{ij} X'_{ij} \geqslant 1\ \forall i \text{ (each Case must be assigned)}\\
&\textstyle\sum_i \sum_{j \in r,t} X'_{ij} \leqslant 1\ \forall r,t \text{ (each Resource can accommodate at most one case)}\\
&Y_r \geqslant \frac{\sum_i \sum_{j \in r} X'_{ij}}{\sum_i (1)}\ (Y_r \text{ definition})\\
&T_i \geqslant S_i - S'_i\ (T_i \text{ definition})\\
&T_i \geqslant -(S_i - S'_i)\ (T_i \text{ definition})\\
&X_{ij} \in \{0,1\}\\
&P_i \in \{0,1\}\\
&Y_r \in \{0,1\}
\end{aligned}$$

satisfies our objective, where the coefficients K_1, K_2, K_3, K_4, and K_5 represent the relative weights placed on the five factors in the objective function. We find that setting $K_1 = 100$ and $K_2 = K_3 = K_4 = K_5 = 1$ succeeds in consolidating rooms while moving relatively few cases and keeping start times as consistent as possible. However, depending on the number of cases performed daily, the number of ORs included in the model, and the importance placed on each factor, the user may change the coefficients as necessary (and view different solutions for the same day using different combinations).

There are limitations to the formulation we have outlined. For example, we do not include constraints to prevent surgeons from having two cases scheduled at the same time in different rooms, nor do we include every possible operational compatibility constraint. These types of constraints are unique to each institution and therefore must be incorporated during the implementation phase. Despite these limitations, ADOPT is still quite robust and efficient, as we will see in the next section.

4.4 Testing the Model

Now that we have outlined the formulation of the model, we will discuss the details of its complexity and performance. In particular, we test the model using four different synthetic scenarios as shown in Table 12. The purpose of the scenario testing is to determine the scalability of the model and to study the change in total solve times required to achieve various levels of optimality with increasing model size (number of rooms and cases). For each of the scenarios, ORs are assumed to run from 7:30 am to 5:00 pm, and no wait list cases are included.

Table 12. Synthetic Scenarios for Testing ADOPT

Scenario	Description
1	22 rooms with 45 cases
2	44 rooms with 87 cases
3	66 rooms with 109 cases
4	88 rooms with 153 cases

In tabulating the results, to highlight the complexity of the model, we report the size of X_{ij} (number of entries) and the total number of decision variables and constraints. We solve each scenario three times, forcing each run to terminate at a specified total solve time between 5 minutes and 30 minutes or when the solution satisfies a specified integer tolerance between 2% and 10%, whichever comes first (the integer tolerance is defined as the difference between the objective of the incumbent solution and the objective of the best bound divided by the objective of the best bound). We check different integer tolerances because integer programs such as the ADOPT formulation can take a large amount of time to verify the optimal (or near-optimal) solution, when these improvements are only marginally beneficial from an operational perspective. In determining the solution, the total solve time is broken into three parts—parse time, problem setup time, and engine solve time—and we set upper bounds on this metric to represent reasonable operational solve times based on the size of the model. The specific total solve time cutoffs and integer tolerance cutoffs for each run are shown in Table 13. We perform all scenario testing on a Dell Optiplex 990 desktop workstation running Windows 7 64-bit operating system with 16GB RAM and a 3.4 GHz Intel Core i7-2600 processor.

One important thing to note is that not all of the X_{ij} entries are included in the model as decision variables. Instead, ADOPT performs adaptive preprocessing so that only X_{ij} entries in which the product duration matches the case duration are included as decision variables. By only including entries with matching durations, we are able to eliminate approximately 95% of the potential decision variables from the X_{ij} matrix—drastically improving the total solve times.

Table 13. ADOPT Scenario Testing Results

Scenario	# of X_{ij} Entries	# of Decision Variables	# of Constraints	Total Solve Time Cutoff (min)	Integer Tolerance Cutoff	Binding Cutoff Criteria	Engine Solve Time (mm:ss)	Improvement over Baseline Objective
1	659,340	28,755	1,039	5	2%	Solve time	4:21	28.4%
				10	5%	Integer tolerance	5:13	28.4%
				15	10%	Integer tolerance	5:11	28.4%
2	2,549,448	114,267	2,065	5	2%	Solve time	1:17	27.1%
				10	5%	Solve time	6:17	29.7%
				15	10%	Solve time	11:15	30.0%
3	4,791,204	212,695	3,011	10	2%	Solve time	0:38	35.0%
				15	5%	Solve time	5:32	35.1%
				20	10%	Solve time	10:16	35.2%
4	8,967,024	404,425	4,045	25	2%	Solve time	3:02	33.8%
				30	5%	Solve time	7:49	33.8%
				35	10%	Solve time	11:32	35.0%

The most important takeaway from the ADOPT scenario testing is that the solutions converge very quickly and do not improve significantly with extended engine solve times (parse times and problem setup times are essentially the same across all runs of the same scenario). For example, we see that for Scenario 1, each of the three runs generates the same percentage improvement over the baseline objective, where the baseline objective is the objective function value for the schedule configuration in place prior to running the model. In addition, we see that for Scenarios 2, 3, and 4, the additional 10 minutes of engine solve time only improve the solution by a few percentage points. ADOPT's ability to converge to near-optimal solutions quickly suggests that OR managers will be able to use the model to make timely decisions in an operational setting. Namely, OR managers will be able to run the model several times each day with different objectives prior to selecting the result that creates the optimal OR schedule upon block release.

4.5 Prototype

As with SPORT, we have developed a prototype graphical user interface for ADOPT (see Figure 7). The prototype uses an API for Frontline Systems' Risk Solver Platform and the Gurobi optimization engine. As we can see in Figure 7, the user can select the OR date in question, view the current schedule, highlight cases that should not be moved, specify time intervals within rooms that should remain unused after the optimization, and view the schedule after optimization is complete. Using this interface, OR managers can determine optimal daily OR schedules with a total solve time of only a few minutes per solution, as demonstrated in the scenario testing results.

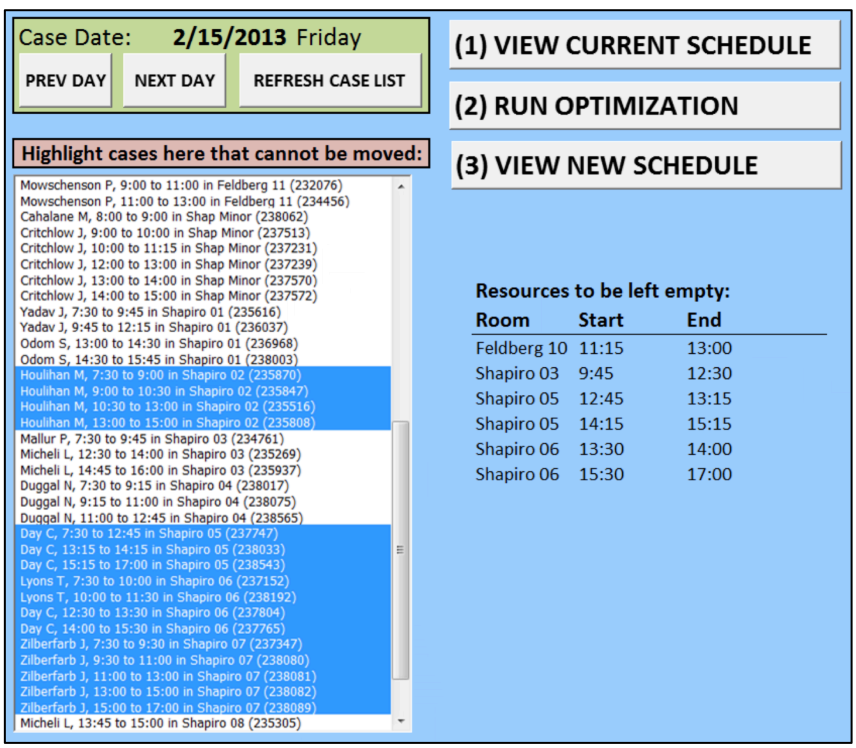


Figure 7. ADOPT Interface

4.6 Example of Optimization Results

In the following section, we will examine how a typical daily OR schedule may appear before and after running ADOPT. In both figures in the following subsections, the columns represent separate rooms, while the rows represent 15-minute time slots between 7:00 am and 7:00 pm. Scheduled blocks are depicted in light gray (with the surgical service written in text), and colored cells represent cases (with a unique case identifier written in text), while the various colors correspond to different surgical services. OR time that does not have a block is depicted in dark gray (e.g., Shapiro 01, 11:00 am – 1:00 pm).

Looking at Figure 8 (OR schedule view prior to optimization), we see that based on the unscheduled block time in this example, the schedule is not very full. This low utilization may be reflective of certain days, while other days may have much more elective surgical demand and show higher levels of utilization. Regardless of how much capacity is available at block release, ADOPT will determine the optimal solution that satisfies the unique objective function that the user specifies.

4.6.1 Current Schedule

Figure 8 depicts which rooms are fully utilized (e.g., Feldberg 04 and Feldberg 05, the fifth and sixth room columns in the figure), and which rooms are partially utilized (e.g., Feldberg 06 and Feldberg 08, the seventh and ninth room columns in the figure). Since anesthesia and nursing staff are typically staffed to an OR for the entire day rather than assigned to individual cases, it makes sense from the hospital's perspective to maximize the utilization of any OR that runs on a particular day so that idle staff time can be kept to a minimum. For this example, the hospital would not want to staff Feldberg 06 and Feldberg 08 for the entire day because this decision would lead to several idle labor hours that generate cost without any supporting revenue. At the same time, the hospital would not want to adjust cases in Feldberg 04 and Feldberg 05 since staffing assignments for those rooms are productive for the entire day due to the full room utilization.

		Cysto 1	Feldberg 01	Feldberg 02	Feldberg 03	Feldberg 04	Feldberg 05	Feldberg 06	Feldberg 07	Feldberg 08	Feldberg 09	Feldberg 10	Feldberg 11	Shap Minor	Shapiro 01	Shapiro 02	Shapiro 03	Shapiro 04	Shapiro 05	Shapiro 06	Shapiro 07
7:00	7:15																				
7:15	7:30																				
7:30	7:45	221773	E.N.T.	225136	224478	223886	223812	UROLOGY	UROLOGY	SURG ONC	221679	223228	224390		220369	PLASTIC SURG	223495	223013	219013	224258	225250
7:45	8:00	221773	E.N.T.	225136	224478	223886	223812	UROLOGY	UROLOGY	SURG ONC	221679	223228	224390		220369	PLASTIC SURG	223495	223013	219013	224258	225250
8:00	8:15	221773	E.N.T.	225136	224478	223886	223812	UROLOGY	UROLOGY	SURG ONC	221679	223228	224390		220369	PLASTIC SURG	223495	223013	219013	224258	225250
8:15	8:30	221773	E.N.T.	225136	224478	223886	223812	UROLOGY	UROLOGY	SURG ONC	221679	223228	224390		220369	PLASTIC SURG	223495	223013	219013	224258	225250
8:30	8:45	221773	E.N.T.	225136	224478	223886	223812	UROLOGY	UROLOGY	SURG ONC	221679	223228	224390		220369	PLASTIC SURG	223495	223013	219013	224258	225250
8:45	9:00	221773	E.N.T.	225136	224478	223886	223812	UROLOGY	UROLOGY	SURG ONC	221679	223228	224390		220369	PLASTIC SURG	223495	223013	219013	224258	225250
9:00	9:15	221773	E.N.T.	225137	224478	223886	223812	UROLOGY	UROLOGY	225400	221679	223228	224390		220369	PLASTIC SURG	223496	223013	219013	224258	225251
9:15	9:30	221773	E.N.T.	225137	224478	223886	223812	UROLOGY	UROLOGY	225400	221679	223228	224390		220369	PLASTIC SURG	223496	223013	219013	224258	225251
9:30	9:45	221773	E.N.T.	225137	224478	223757	223812	UROLOGY	UROLOGY	225400	221679	223228	224390		OPHTHALMO	PLASTIC SURG	223496	223013	219295	224258	225251
9:45	10:00	221773	E.N.T.	225137	224478	223757	224166	UROLOGY	UROLOGY	225400	221679	223228	224390		OPHTHALMO	PLASTIC SURG	223496	223013	219295	224258	225251
10:00	10:15	222952	E.N.T.	225137	224478	223757	224166	UROLOGY	UROLOGY	225400	221679	223228	224390		OPHTHALMO	PLASTIC SURG	223496	223013	219295	224255	225251
10:15	10:30	222952	E.N.T.	225137	224478	223757	224166	UROLOGY	UROLOGY	225400	221679	223228	224390		OPHTHALMO	PLASTIC SURG	223496	223013	219295	224255	225251
10:30	10:45	222952	E.N.T.	221418	224478	223757	224166	UROLOGY	UROLOGY	225400	221679	223228	224390		OPHTHALMO	PLASTIC SURG	225087	223013	219295	224255	225251
10:45	11:00	222952	E.N.T.	221418	224478	223757	224166	UROLOGY	UROLOGY	225400	221679	223229	224390		OPHTHALMO	PLASTIC SURG	225087	223013	219295	224255	225251
11:00	11:15	222952	E.N.T.	221418	224478	223757	224166	UROLOGY	UROLOGY	225401	OB/GYN	223229	224390			PLASTIC SURG	225087	217517	219295	224255	225251
11:15	11:30	222952	E.N.T.	221418	224478	223757	224166	UROLOGY	UROLOGY	225401	OB/GYN	223229	224390			PLASTIC SURG	225087	217517	219295	224255	225252
11:30	11:45	222952	E.N.T.	221418	224478	223757	224166	UROLOGY	UROLOGY	225401	OB/GYN	223229	224390			PLASTIC SURG	225087	217517	219301	224255	225252
11:45	12:00	222952	E.N.T.	221418	224478	223757	224166	UROLOGY	UROLOGY	225401	OB/GYN	223229	224390			PLASTIC SURG	225087	217517	219301	224255	225252
12:00	12:15	222952	E.N.T.	221418	224478	223757	224907	UROLOGY	UROLOGY	225401	OB/GYN	223229	224390				225087	217517	219301	224255	225252
12:15	12:30	222952	E.N.T.	221418	224478	223757	224907	UROLOGY	UROLOGY	225401	OB/GYN	223229	224390				225087	217517	219301	224255	225252
12:30	12:45	224152	E.N.T.	221418	UROLOGY	223759	224907	UROLOGY	UROLOGY	225401	OB/GYN	223229	224390				225087	217517	219301	224255	225252
12:45	13:00	224152	E.N.T.	221418	UROLOGY	223759	224907	UROLOGY	UROLOGY	225401	OB/GYN	223229	224390				225155	217517	219301	220999	225252
13:00	13:15	224152	224867	221418	UROLOGY	223759	224907	224872	UROLOGY	SURG ONC	OB/GYN	223229	224390		224462	PLASTIC SURG	225155	217517	219301	220999	
13:15	13:30	224152	224867	221418	UROLOGY	223759	224907	224872	UROLOGY	SURG ONC	OB/GYN	223229	224390		224462	PLASTIC SURG	225155	217517	219301	220999	
13:30	13:45	224152	224867	221418	UROLOGY	223759	224907	224872	UROLOGY	SURG ONC	OB/GYN	223229	224390		224462	PLASTIC SURG	225155	223514	218735	220999	
13:45	14:00	224152	224867	221418	UROLOGY	223759	224907	224872	UROLOGY	SURG ONC	OB/GYN	223229	224390		224462	PLASTIC SURG	225155	223514	218735	220999	
14:00	14:15	224152	224867	221418	UROLOGY	223759	224907	224872	UROLOGY	SURG ONC	225404	223230	224390		222611	PLASTIC SURG	225155	223514	218735	220999	
14:15	14:30	224152	224867	221418	UROLOGY	223759	224907	224872	UROLOGY	SURG ONC	225404	223230	224390		222611	PLASTIC SURG	ORTHOPEDIC	223514	218735	220999	
14:30	14:45	224152	224867	221418	UROLOGY	223761	224907	224872	UROLOGY	SURG ONC	225404	223230	224390		222611	PLASTIC SURG	ORTHOPEDIC	223514	218735	220999	
14:45	15:00	224152	224867	221418	UROLOGY	223761	224907	224872	UROLOGY	SURG ONC	225404	223230	224390		222611	PLASTIC SURG	ORTHOPEDIC	223514	218735	225049	
15:00	15:15	224601	224867	221418	UROLOGY	223761	224907	224872	UROLOGY	SURG ONC	225404	223230	224390		222841	PLASTIC SURG	ORTHOPEDIC	223514	218735	225049	
15:15	15:30	224601	224867	221418	UROLOGY	223761	224907	224872	UROLOGY	SURG ONC	225404	223230	224390		222841	PLASTIC SURG	ORTHOPEDIC	223514	224424	225049	
15:30	15:45	224601	224867	221418	UROLOGY	223761	224907	224872	UROLOGY	SURG ONC		223230	224390		222841	PLASTIC SURG	ORTHOPEDIC	ORTHOPEDIC	224424	225049	
15:45	16:00	224601	224867	221418	UROLOGY	223761	224907	UROLOGY	UROLOGY	SURG ONC		223230	224390		222841	PLASTIC SURG	ORTHOPEDIC	ORTHOPEDIC	224424	225049	
16:00	16:15	224601	224867	PLASTIC SURG	UROLOGY	223891	224907	UROLOGY	UROLOGY	SURG ONC		223230	224390		224480	PLASTIC SURG	ORTHOPEDIC	ORTHOPEDIC	224424	225049	
16:15	16:30	UROLOGY	224867	PLASTIC SURG	UROLOGY	223891	224907	UROLOGY	UROLOGY	SURG ONC		223230	224390		224480	PLASTIC SURG	ORTHOPEDIC	ORTHOPEDIC	224424	225049	
16:30	16:45	UROLOGY	224867	PLASTIC SURG	UROLOGY	223891	224907	UROLOGY	UROLOGY	SURG ONC		223230	PLASTIC SURG		224480	PLASTIC SURG	ORTHOPEDIC	ORTHOPEDIC		225049	
16:45	17:00	UROLOGY	224867	PLASTIC SURG	UROLOGY	223891	224907	UROLOGY	UROLOGY	SURG ONC		223230	PLASTIC SURG		224480	PLASTIC SURG	ORTHOPEDIC	ORTHOPEDIC		ORTHOPEDIC	
17:00	17:15		224867				224907		UROLOGY												
17:15	17:30		224867				224907		UROLOGY												
17:30	17:45		224867				224907		UROLOGY												
17:45	18:00		224867				224907		UROLOGY												
18:00	18:15						224907		UROLOGY												
18:15	18:30						224907		UROLOGY												
18:30	18:45								UROLOGY												
18:45	19:00								UROLOGY												

Figure 8. Daily OR Schedule View (Prior to Running ADOPT)

4.6.2 Optimized Schedule

Figure 9 presents the optimized schedule after running ADOPT. The orange arrows show the moves that were made (previous locations are lightly shaded). One case was brought onto the schedule from the wait list at the end of the day in Feldberg 09 (the tenth room column in the figure). Most importantly, however, are the white arrows, which demonstrate that 3 ORs (Feldberg 03, Feldberg 06, and Feldberg 08) were closed via room consolidation. By closing those rooms, staff that otherwise would have been assigned to those locations can now confidently dedicate their day to non-clinical duties, flex their time to work on a busier day, or take the day off. Taking advantage of these potential staffing enhancements by means of automated schedule optimization in advance of the day of surgery has the potential to increase labor productivity dramatically while saving hospitals hundreds of thousands of dollars per year in avoidable idle time and overtime costs.

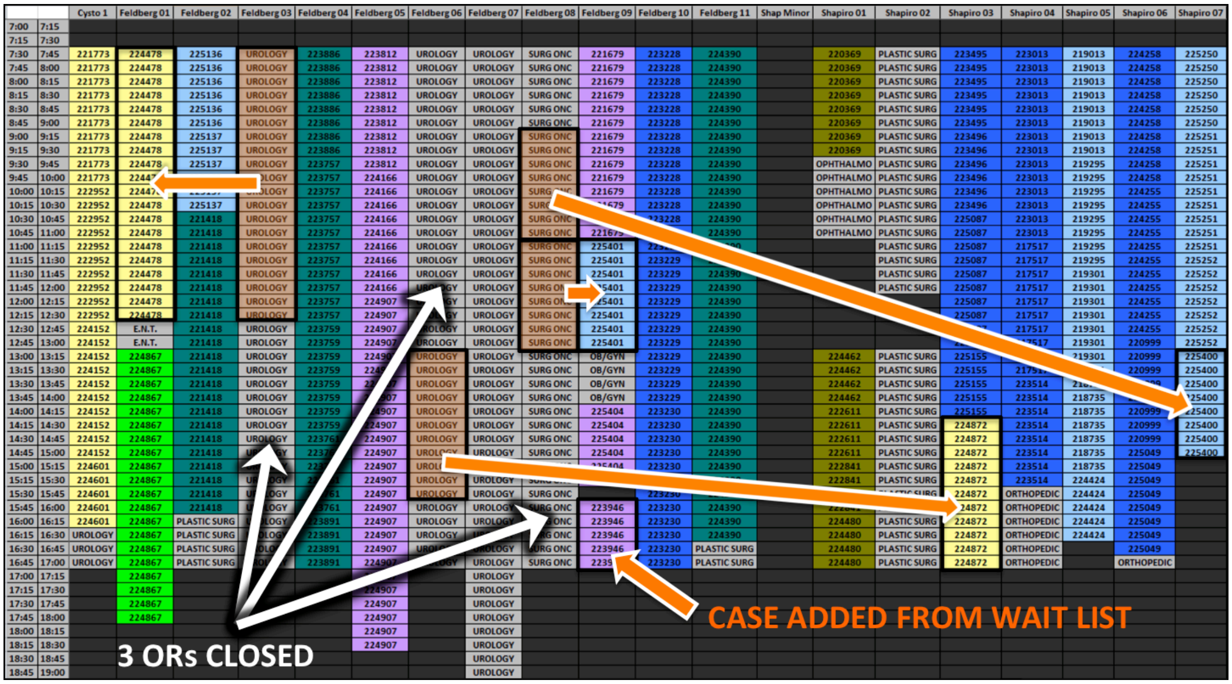


Figure 9. Daily OR Schedule View (Optimized Via Running ADOPT)

4.7 Improvement over Current Process

As we have shown, the benefits of ADOPT are primarily related to the ability to shuffle cases in a systematic manner. However, we have also pointed out that moving cases is not a simple task due to operational constraints and political barriers. To conclude this chapter, we will highlight the way we believe ADOPT can be used effectively in an OR scheduling department and how an automated schedule optimization system improves upon the current schedule optimization process.

Since shuffling cases typically requires moving cases into nonstandard blocks, it is not feasible to use ADOPT prior to block release since block owners are free to schedule cases into their blocks up to the time of release. Instead, we propose that OR scheduling managers use ADOPT at the moment of block release to assess a number of optimized schedules (some may minimize rooms running, while others may maximize surgeon preferences or meet a mixed objective). For a reasonably sized OR system, each iteration of ADOPT only takes a few minutes to run, so the OR scheduling manager can view and analyze the differences between three or four optimized schedules in half an hour before making a decision.

As we described earlier, most hospitals typically have an individual that is responsible for managing the daily OR schedule. Upon block release, this person manually scans the schedule and looks for opportunities to consolidate rooms or move cases to maximize staff productivity and resource utilization. As such, this tedious task varies in complexity from one day to the next and relies on human intuition and experience rather than a systematic process. While human judgment is necessary to run an OR system effectively, it is highly unlikely that humans can generate optimal results as quickly and consistently as a standardized optimization routine. Therefore, ADOPT provides a way to guarantee the solution that the user desires while giving the user different options to view and consider. We believe that OR managers will be interested in using ADOPT because it protects their ability to make decisions while giving them a finite list of schedule options so they can use their intuition more effectively.

5 Future Work and Conclusions

SPORT and ADOPT represent data-driven analytical tools that improve the way hospitals utilize their OR resources. We have developed prototypes of each tool that are fully functional. In fact, at the time of this thesis, SPORT is being used at the host institution with which we collaborated to perform the research and development work. However, both tools can be further refined to become more useful, robust, and reliable. This chapter will discuss future work considerations related to both tools, highlight a comparison between OR scheduling and the airline ticket booking process, and conclude with a summary of the long-term impact of employing these tools at medical institutions.

5.1 SPORT: Future Work

As mentioned, SPORT has passed the testing phase and OR managers are using the tool to confirm non-block cases early and make resource planning decisions. However, there are still some modifications to the system that could improve the forecast accuracy. Below is a list of these modifications:

1. Verify whether multiple linear regression is the most appropriate model selection. One area of future work is to test other types of models to determine whether they can generate more accurate predictions than the model we have proposed. Despite being more computationally complex, other techniques such as time series modeling and machine learning may help hospitals further mitigate the risks of making case confirmations in advance.
2. Eliminate holidays from the historical dataset. When aggregating data over the previous six months, SPORT considers every observation of the same day of the week (regardless of how much OR time was used). Holidays that fall during the week typically result in

many fewer minutes of surgery since ORs are generally closed to elective cases on those days. Excluding holidays from the model appropriately takes these low-time days out of consideration, resulting in forecasts that are more accurate.

3. Include early release of block time in the forecast. When surgeons have other commitments and know that they will not be able to use their block, they are able to release their block time in advance and make it available to other surgeons. SPORT can be made more robust by running the prediction model excluding historical booking information for surgeons who have released their blocks. Since the known released time is *guaranteed* to be available, it can be added separately to the predicted availability.
4. Ensure that unusable OR time is not considered available. Sometimes, buffers are built into the OR schedule in which time cannot be used. For example, if a surgeon operates in two rooms, he or she will go back and forth between the rooms to perform the cases, but there will be unused "stagger time" between cases that is not available to schedule other cases. The model should be modified to realize that this time is unusable and consider it unavailable.
5. Understand the distribution of time intervals within the total amount of predicted available OR time. SPORT outputs a prediction of total available OR capacity, which only partially translates to usable capacity. For instance, we know that a 4-hour case requires 4 *continuous* hours of OR time. OR managers attempting to confirm a 4-hour case may not realize that when SPORT predicts 4 hours of availability, that time could be spread across multiple rooms with no more than 1 hour of availability in any particular room. Developing the capability to understand the distribution of time intervals within the predictions is a critical next step in enhancing the value of the system.

Another area of future work for SPORT involves developing more accurate representations of surgical demand and OR access. In particular, one of the limitations of using historical booking information to predict future demand (or the need to attract additional demand) is that the historical records do not accurately reflect unrestricted demand because they do not account for spilled (unrealized) demand. In fact, the historical records only provide a lower bound on demand. As such, an area for future research is to develop a spill model that can be used to determine whether additional demand exists in the market to fill in the schedule gaps that SPORT identifies in advance of the day of surgery.

Finally, in the current healthcare marketplace, provider sites have been consolidating—that is, joining forces to operate as a single system rather than individual organizations—in an effort to pool their resources and provide care at a lower cost. Research indicates that these trends will continue [19], [36]. If multi-hospital systems were to employ SPORT, they could use the tool to forecast demand for multiple OR systems, allocate resources between these systems, and transfer surgical cases (or allocate staff) between locations. However, the tools would need to be modified to predict and optimize multiple OR systems. To do so, the large network organization would integrate all of its OR demand into a single SPORT installation. This work would entail gathering booking data from multiple sources, predicting utilization at the different locations, and allowing some surgeries to be moved across locations. If SPORT and ADOPT were modified to function together in this way, they would connect multiple sites to obtain information about system-level expected demand and give managers the knowledge they need to coordinate care effectively between locations and realize more efficient resource utilization.

5.2 ADOPT: Future Work

Currently, we have a working prototype of ADOPT as described in Chapter 4. However, we have not yet incorporated all the constraints to make the system fully functional. The following list shows the work that needs to be done to realize the complete operational benefit of a daily OR schedule optimization tool.

1. Build functionality on the user interface to allow users to set objective function coefficients based on their relative weight. This functionality (for example, scroll bars) will make it easy for users to optimize the schedule for different objectives.
2. Determine the full list of incompatible room/case combinations to populate zeros dynamically within M_{ij}. This list of incompatibilities must be updated when OR functionality changes or new procedures are added.
3. Gain a complete understanding of surgeon preferences and operational preferences. To run ADOPT effectively, it is critical to know which ORs each surgeon prefers as well as which types of cases are better suited for certain rooms based on room setup and the storage location of required equipment. This information typically resides inside OR managers' minds, and when quantified, serves as the basis for determining C_{ij} entries dynamically. The knowledge must be kept up-to-date, particularly as new surgeons join the institution and impose operational changes that affect preferences.
4. Build staffing constraints into the model. Since nursing and anesthesia have staffing limits and specialization restrictions, ADOPT must consider these limitations when optimizing the schedule.

Another area of future work within ADOPT is to incorporate financial data within the optimization model. Currently, we only consider operational efficiency and surgeon preferences, but neither of these aspects have a direct relationship with financial implications. It would be very useful to include basic financial information for each case (such as expected contribution per OR hour) as another objective when comparing schedules. However, when employing financial data, one must remember that the financial aspects related to a surgical patient depend on more than just the procedure that takes place in the OR. Each patient goes through a care delivery process that includes pre-admission testing, preoperative care, and postoperative care, so surgery is only a part of the process. A revenue-maximizing or profit-maximizing model must connect surgical cases with the care delivery process of each patient to determine how decisions regarding the use of OR time will impact the entire system financially.

5.3 Comparison Between OR Scheduling and Airline Ticket Booking

Interestingly, the use of OR demand forecasting to drive SPORT is quite analogous to the forecasting methods that airlines use to sell tickets for their flights. In particular, airlines' revenue management systems use statistical models and demand forecasts for each fare class to set booking limits on the number of tickets in each fare class that can be sold at a particular point in time. The purpose of these revenue management systems is to protect some of the higher-priced business fares until later in the booking process when the corresponding passengers are typically ready to purchase. Without having a revenue management system in place, if leisure demand is high, the airline may run the risk of selling all of its seats to passengers who purchase discounted fares, maximizing the number of tickets sold but lowering the total revenue that each flight generates. Thus, revenue management systems have a dramatic impact on airlines' profitability. Since the airline industry is a marginally profitable industry on the whole, these types of systems are a critical part of an airline's financial viability.

As we know from experience, it is common practice for airlines to overbook their flights—that is, allow more tickets to be purchased than the total seat capacity—to take advantage of the fact that not all ticketed passengers will show up to the gate at the time of the flight. The tradeoff at play for airlines is the comparison between the costs of a denied boarding (which occurs when more passengers show up than then number of seats available on the flight), and the costs of spoilage (which represents the missed revenue opportunity for seats that go unoccupied that could have been filled if the airline had authorized more bookings). Specifically, an airline's objective is to minimize the total combined cost of denied boardings and spoilage.

The overbooking tradeoff that airlines face is vastly similar to the tradeoff analysis that we outlined in Chapter 3 regarding OR managers' use of OR time availability predictions, where they must minimize the combined risks of overbooking the OR schedule and missing the opportunity to add cases into available OR capacity. However, the major caveat for hospitals is the fact that patients, unlike airline travelers, cannot simply be denied service in an overbooking scenario. Factors such as substantial patient preparation requirements (e.g., not eating or drinking in the hours prior to the procedure), urgent clinical need for surgery, and the lack of available capacity on subsequent OR dates make it more difficult to deny a surgery than a seat on a flight. Put quantitatively, this observation translates into the general understanding that the costs of denying surgeries are much higher than the costs of missing the opportunity to use available OR time. However, as we will see, even with this understanding, the costs of denying surgeries are certainly finite and can be evaluated.

While aircraft have a fixed seat capacity that absolutely cannot be exceeded, when we describe overbooking the OR schedule, we typically mean that more OR time is booked than the amount of allotted block capacity that is available on a particular day. Interestingly, however, the allotted block capacity is by definition less than the total theoretical capacity of the OR system. Given that this is the case, instead of denying (or "bumping") surgeries from the OR schedule, hospitals can run cases beyond the block schedule. In fact, OR delays cause cases to run beyond the end of their scheduled block on a regular basis. With this in mind, the question then becomes whether the schedule disruption cost from booking surgeries beyond the allotted block capacity is greater than the amount of incremental revenue that can be generated as a result of performing the additional cases. In reality, the rates at which insurance providers reimburse surgical procedures suggest that incremental revenues are more valuable, implying that hospitals should take on some risk in booking the OR schedule slightly beyond the block capacity in order to capture incremental volume that could otherwise spill to another institution. However, in practice, we typically see the opposite effect: OR scheduling managers tend to err on the conservative side when booking surgeries so as not to overbook the schedule.

While running cases beyond the allotted block capacity is likely to turn a positive profit for hospitals, the intangible costs of doing so cannot be ignored. In particular, OR staff members' morale can decrease over time if cases continually run beyond the end of their shift, causing unpredictable schedules. The low morale may lead to higher staff turnover, which will drive up costs in recruiting and training. In addition, surgeons may become dissatisfied if their cases routinely start late in the evening at a particular institution, and this frustration may cause them to take their patients to other facilities. The lost volume in this scenario also results in a negative financial outcome.

Despite not having an established model to compare overbooking costs with the opportunity costs of not using available OR time, hospitals should be evaluating this tradeoff continually. The results of such analyses, particularly if backed by senior leadership and framed properly for each stakeholder group, have the potential to change surgical scheduling behavior and improve OR profitability in the same way airlines gain significant financial benefit from revenue management systems.

5.4 Summary and Conclusions

SPORT and ADOPT represent a set of analytical tools that have the potential to bring long-term operational improvements and financial gains to hospitals and surgery centers. We have demonstrated the problem of fluctuating demand and shown how predictive analytics and schedule optimization techniques can be used to anticipate these fluctuations and respond accordingly.

SPORT and ADOPT comprise flexible solutions that users can customize to meet changing organizational priorities (such as adjusting the allotment of block time between surgical services) or the desired level of risk of the predictions. In addition, SPORT and ADOPT have been created in a generalizable fashion and can be configured to conform to the needs, constraints, and clinical limitations of any OR setting.

We believe that the use of SPORT and ADOPT will contribute to revenue growth through the ability to recruit additional cases when the forecasts show available time. In addition to revenue growth, the tools can also reduce variable labor costs by helping managers modulate staffing levels more than one week prior to the day of surgery to match the expected caseload. However, to realize these gains, any institution that wants to employ these types of tools must be mindful of the need for proper communication and training. While the tools have analytical engines that can bring significant efficiency gains, any implementation will not succeed without a communication plan to send to surgeons and staff to explain the required workflow changes. In addition, staff will need to be trained to interpret the results and learn how to use the knowledge to make decisions. To meet operational and financial goals with the adoption of these tools, the approach to framing the problem, communicating the solution, and incorporating staff into the target workflow process is just as important as the set of analytical solutions. Ultimately, when implemented properly, SPORT and ADOPT generate a higher degree of schedule predictability than the current surgical scheduling system allows, which translates to higher satisfaction for patients, physicians, and staff at healthcare organizations.

References

[1] Belien, J., E. Demeulemeester, B. Cardoen. 2009. A Decision Support System for Cyclic Master Surgery Scheduling with Multiple Objectives. *Journal of Scheduling* 12(2): 147-161.

[2] Blake, J. T., J. Donald. 2002. Operating Room Managers' Use of Integer Programming for Assigning Block Time to Surgical Groups: A Case Study. *Anesthesia and Analgesia* 94(1): 143-148.

[3] Blake, J. T., J. Donald. 2002. Mount Sinai Hospital Uses Integer Programming to Allocate Operating Room Time. *Interfaces* 32(2): 63-73.

[4] Calichman, M. V. 2005. Creating an Optimal Operating Room Schedule. *AORN Journal* 81(3): 580-588.

[5] Cardoen, B., E. Demeulemeester, J. Belien. 2009. Optimizing a Multiple Objective Surgical Case Sequencing Problem. *International Journal of Production Economics* 119(2): 354-366.

[6] Charnetski, J. R. 1984. Scheduling Operating Room Surgical Procedures with Early and Late Completion Penalty Costs. *Journal of Operations Management* 5(1): 91-102.

[7] Cromwell, J., J. Mitchell. 1986. Physician-induced Demand for Surgery. *Journal of Health Economics* 5(4): 293-313.

[8] Denton, B., J. Viapiano, A. Vogl. 2007. Optimization of Surgery Sequencing and Scheduling Decisions Under Uncertainty. *Health Care Management Science* 10(1): 3-24.

[9] Dexter, F., D. A. Lubarsky, J. T. Blake. 2002. Sampling Error Can Significantly Affect Measured Hospital Financial Performance of Surgeons and Resulting Operating Room Time Allocations. *Anesthesia and Analgesia* 95(1): 184-188.

[10] Dexter, F., A. Macario. 2002. Changing Allocations of Operating Room Time from a System Based on Historical Utilization to One Where the Aim is to Schedule as Many Surgical Cases as Possible. *Anesthesia and Analgesia* 94(5): 1272-1279.

[11] Dexter, F., A. Macario, D. A. Lubarsky, D. D. Burns. 1999. Statistical Method to Evaluate Management Strategies to Decrease Variability in Operating Room Utilization—Application of Linear Stastical Modeling and Monte-Carlo Simulation to Operating Room Management. *Anesthesiology* 91(1): 262-274.

[12] Dexter, F., A. Macario, R. Traub, D. Lubarsky. 2003. Operating Room Utilization Alone Is Not an Accurate Metric for the Allocation of Operating Room Block Time to Individual Surgeons with Low Caseloads. *Anesthesiology* 98(5): 1243-1249.

[13] Dexter, F., A. Macario, F. Qian, R. D. Traub. 1999. Forecasting Surgical Groups Total Hours of Elective Cases for Allocation of Block Time. Application of Time Series Analysis to Operating Room Management. *Anesthesiology* 91(1): 262-274.

[14] Dexter, F., A. Macario, R. D. Traub. 1999. Which Algorithm for Scheduling Add-on Elective Cases Maximizes Operating Room Utilization? Use of Bin-packing Algorithms and Fuzzy Constraints in Operating Room Management. *Anesthesiology* 91(5): 1491-1500.

[15] Dexter, F., A. Macario, R. D. Traub, M. Hopwood, D. A. Lubarsky. 1999. An Operating Room Scheduling Strategy to Maximize the Use of Operating Room Block Time:

Computer Simulation of Patient Scheduling and Survey of Patients' Preferences for Surgical Waiting Time. *Anesthesia and Analgesia* 89(1): 7-20.

[16] Dexter, F., R. Traub. 2002. How to Schedule Elective Surgical Cases into Specific Operating Rooms to Maximize the Efficiency of Use of Operating Room Time. *Anesthesia and Analgesia* 94(4): 933-942.

[17] Epstein, R. H., F. Dexter. 2002. Statistical Power Analysis to Estimate How Many Months of Data Are Required to Identify Operating Room Staffing Solutions to Reduce Labor Costs and Increase Productivity. *Anesthesia and Analgesia* 94(3): 640-643.

[18] Escarce, J. 1993. Effects of the Relative Fee Structure on the Use of Surgical Operations. *Health Services Research* 28(4): 479-502.

[19] Goldstein, L. 2012. The New Wave of Hospital Consolidation. *Journal of the Healthcare Financial Management Association* 66(4): 60-67.

[20] Gupta, D., B. Denton. 2008. Appointment Scheduling in Health Care: Challenges and Opportunities. *IIE Transactions* 40(9): 800-819.

[21] Kuo, P. C., R. A. Schroeder, S. Mahaffey, R. R. Bollinger. 2003. Optimization of Operating Room Allocation Using Linear Programming Techniques. *Journal of the American College of Surgeons* 197(6): 889-895.

[22] Lamiri, M., F. Grimaud, X. Xie. 2009. Optimization Methods for a Stochastic Surgery Planning Problem. *International Journal of Production Economics* 120(2): 400-410.

[23] Lamiri, M., X. Xie, A. Dolgui, F. Grimaud. 2008. A Stochastic Model for Operating Room Planning with Elective and Emergency Demand for Surgery. *European Journal of Operational Research* 185(3): 1026-1037.

[24] Litvak, E., M. Bisognano. 2011. More Patients, Less Payment: Increasing Hospital Efficiency in the Aftermath of Health Reform. *Health Affairs* 30(1): 76-80.

[25] May, J., W. Spangler, D. Strum, L. Vargas. 2011. The Surgical Scheduling Problem: Current Research and Future Opportunities. *Production and Operations Management* 20(3): 392-405.

[26] McManus, M., M. Long, A. Cooper, J. Mandell, D. Berwick, M. Pagano, E. Litvak. 2003. Variability in Surgical Caseload and Access to Intensive Care Services. *Anesthesiology* 98(6): 1491-1496.

[27] Ogulata, S. N., R. Erol. 2003. A Hierarchical Multiple Criteria Mathematical Programming Approach for Scheduling General Surgery Operations in Large Hospitals. *Journal of Medical Systems* 27(3): 259-270.

[28] Ozkarahan, I. 2000. Allocation of Surgeries to Operating Rooms by Goal Programming. *Journal of Medical Systems* 24(6): 339-378.

[29] Pandit, J. J., M. Pandit, J. M. Reynard. 2010. Understanding Waiting Lists as the Matching of Surgical Capacity to Demand: Are We Wasting Enough Surgical Time? *Anaesthesia* 65(6): 625-640.

[30] Pham, D-N., A. Klinkert. 2008. Surgical Case Scheduling as a Generalized Job Shop Scheduling Problem. *European Journal of Operational Research* 185(3): 1011-1025.

[31] Sham, Gregory C. 2012. Developing a Data-Driven Approach for Improving Operating Room Scheduling Processes. Massachusetts Institute of Technology. LGO Master's Thesis.

[32] Strum, D. P., L. G. Vargas, J. H. May, G. Bashein. 1997. Surgical Suite Utilization and Capacity Planning: A Minimal Cost Analysis Model. *Journal of Medical Systems* 21(5): 309-322.

[33] Velásquez, R., M. T. Melo. 2006. A Set Packing Approach for Scheduling Elective Surgical Procedures. In H.-D. Haasis, J. Kopfer, and J. Schönberger (Eds.). *Operations Research Proceedings 2005: Selected Papers of the Annual International Conference of the German Operations Research Society (GOR).* Bremen, September 7-9, 2005. Berlin: Springer-Verlag, pp. 425-430.

[34] Vermeulen, I. B., S. M. Bohte, S. G. Elkhuizen, H. Lameris, P. J. M. Bakker, H. La Poutre. 2009. Adaptive Resource Allocation for Efficient Patient Scheduling. *Artificial Intelligence in Medicine* 46(1): 67-80.

[35] Wachtel, R. E., F. Dexter. 2008. Tactical Increases in Operating Room Block Time for Capacity Planning Should Not be Based on Utilization. *Anesthesia and Analgesia* 106(1): 215-226.

[36] Wechsler, J. 2011. Regulators Review Market Consolidation. *Managed Healthcare Executive* 21(10): 5-6.

[37] Zhang, M., P. Murali, M. Dessouky, D. Belson. 2009. A Mixed Integer Programming Approach for Allocating Operating Room Capacity. *The Journal of the Operational Research Society* 60(5): 663-673.

[38] (No authors listed). 2004. Boston Hospital Sees Big Impact from Smoothing Elective Schedule. *OR Manager* 20(12): 1, 10-12.

Appendix A (Cross-Validation Results)

Model 1:

Run # (i)	Obs. # left out	In-sample R^2	In-sample Adj R^2	Y_i	Modeled Y_i	Residual	Percent Error (Abs. Value)	SS_err_i	SS_tot_i
1	30	0.671	0.617	1950	1431.26	518.74	36.24%	269087	87320
2	1	0.669	0.613	1785	2237.20	-452.20	20.21%	204485	212060
3	2	0.652	0.595	1815	1749.70	65.30	3.73%	4264	185330
4	3	0.665	0.609	2160	2432.18	-272.18	11.19%	74082	7310
5	4	0.597	0.530	855	1322.99	-467.99	35.37%	219018	1933490
6	5	0.669	0.614	1830	2279.19	-449.19	19.71%	201768	172640
7	6	0.694	0.644	2280	2981.73	-701.73	23.53%	492425	1190
8	7	0.626	0.563	3210	3014.92	195.08	6.47%	38058	930260
9	8	0.667	0.612	2655	3086.16	-431.16	13.97%	185897	167690
10	9	0.666	0.610	2835	3351.07	-516.07	15.40%	266328	347510
11	10	0.735	0.691	2580	1554.14	1025.86	66.01%	1052398	111890
12	11	0.663	0.607	2370	2134.19	235.81	11.05%	55606	15500
13	12	0.672	0.617	2895	2325.77	569.23	24.47%	324022	421850
14	13	0.655	0.598	2670	2486.43	183.57	7.38%	33699	180200
15	14	0.643	0.583	1290	1745.20	-455.20	26.08%	207206	912980
16	15	0.664	0.608	2385	2135.94	249.06	11.66%	62030	19460
17	16	0.652	0.594	2730	2599.37	130.63	5.03%	17063	234740
18	17	0.658	0.601	1740	2047.98	-307.98	15.04%	94855	255530
19	18	0.677	0.623	2580	2063.13	516.87	25.05%	267159	111890
20	19	0.648	0.589	3030	2676.84	353.16	13.19%	124721	615440
21	20	0.666	0.611	2535	2186.50	348.50	15.94%	121450	83810
22	21	0.658	0.601	2490	2617.08	-127.08	4.86%	16148	59780
23	22	0.622	0.559	1065	1514.79	-449.79	29.69%	202308	1393580
24	23	0.679	0.626	2595	2080.11	514.89	24.75%	265115	122150
25	24	0.661	0.605	2445	2238.72	206.28	9.21%	42549	39800
26	25	0.667	0.612	1680	2159.63	-479.63	22.21%	230044	319790
27	26	0.647	0.588	1650	1745.35	-95.35	5.46%	9092	354620
28	27	0.658	0.601	2790	2447.25	342.75	14.01%	117480	296480
29	28	0.657	0.599	1680	2005.68	-325.68	16.24%	106067	319790
30	29	0.648	0.589	2790	2796.41	-6.41	0.23%	41	296480
total								5304466	10210568
						Model 1	Out-of-sample R^2:		0.480

Model 2:

Run # (i)	Obs. # left out	In-sample R^2	In-sample Adj R^2	Y_i	Modeled Y_i	Residual	Percent Error (Abs. Value)	SS_err_i	SS_tot_i
1	30	0.667	0.627	1950	1398.52	551.48	39.43%	304127	87320
2	1	0.655	0.614	1785	2127.73	-342.73	16.11%	117467	212060
3	2	0.646	0.603	1815	1767.04	47.96	2.71%	2300	185330
4	3	0.660	0.620	2160	2473.47	-313.47	12.67%	98266	7310
5	4	0.590	0.541	855	1339.57	-484.57	36.17%	234812	1933490
6	5	0.654	0.613	1830	2130.73	-300.73	14.11%	90437	172640
7	6	0.694	0.658	2280	2998.59	-718.59	23.96%	516367	1190
8	7	0.622	0.576	3210	2931.97	278.03	9.48%	77302	930260
9	8	0.665	0.625	2655	3132.04	-477.04	15.23%	227571	167690
10	9	0.659	0.618	2835	3349.67	-514.67	15.36%	264885	347510
11	10	0.701	0.665	2580	1812.43	767.57	42.35%	589158	111890
12	11	0.656	0.614	2370	2145.02	224.98	10.49%	50617	15500
13	12	0.671	0.631	2895	2295.16	599.84	26.14%	359811	421850
14	13	0.648	0.606	2670	2496.66	173.34	6.94%	30048	180200
15	14	0.636	0.593	1290	1753.75	-463.75	26.44%	215068	912980
16	15	0.658	0.616	2385	2122.47	262.53	12.37%	68920	19460
17	16	0.647	0.605	2730	2534.87	195.13	7.70%	38076	234740
18	17	0.655	0.613	1740	2096.16	-356.16	16.99%	126850	255530
19	18	0.668	0.628	2580	2097.51	482.49	23.00%	232800	111890
20	19	0.644	0.601	3030	2636.04	393.96	14.95%	155206	615440
21	20	0.660	0.619	2535	2179.64	355.36	16.30%	126280	83810
22	21	0.651	0.609	2490	2624.59	-134.59	5.13%	18114	59780
23	22	0.614	0.568	1065	1517.43	-452.43	29.82%	204695	1393580
24	23	0.672	0.632	2595	2088.34	506.66	24.26%	256709	122150
25	24	0.656	0.614	2445	2205.85	239.15	10.84%	57193	39800
26	25	0.655	0.613	1680	2074.35	-394.35	19.01%	155509	319790
27	26	0.640	0.597	1650	1772.33	-122.33	6.90%	14963	354620
28	27	0.647	0.605	2790	2534.76	255.24	10.07%	65149	296480
29	28	0.650	0.608	1680	2011.48	-331.48	16.48%	109878	319790
30	29	0.641	0.598	2790	2814.44	-24.44	0.87%	597	296480
total								4809175	10210568
						Model 2	Out-of-sample R^2:		0.529

Model 3:

Run # (i)	Obs. # left out	In-sample R^2	In-sample Adj R^2	Y_i	Modeled Y_i	Residual	Percent Error (Abs. Value)	SS_err_i	SS_tot_i
1	30	0.339	0.289	1950	2560.44	-610.44	23.84%	372636	87320
2	1	0.344	0.294	1785	2457.90	-672.90	27.38%	452792	212060
3	2	0.306	0.253	1815	2013.27	-198.27	9.85%	39312	185330
4	3	0.332	0.281	2160	2591.85	-431.85	16.66%	186497	7310
5	4	0.240	0.182	855	1786.67	-931.67	52.15%	868008	1933490
6	5	0.342	0.291	1830	2458.94	-628.94	25.58%	395570	172640
7	6	0.358	0.308	2280	2992.70	-712.70	23.81%	507947	1190
8	7	0.346	0.295	3210	2163.86	1046.14	48.35%	1094401	930260
9	8	0.309	0.255	2655	2880.62	-225.62	7.83%	50906	167690
10	9	0.319	0.267	2835	2294.21	540.79	23.57%	292459	347510
11	10	0.320	0.268	2580	2225.10	354.90	15.95%	125954	111890
12	11	0.328	0.277	2370	1975.19	394.81	19.99%	155879	15500
13	12	0.309	0.256	2895	2403.13	491.87	20.47%	241940	421850
14	13	0.303	0.250	2670	2677.94	-7.94	0.30%	63	180200
15	14	0.263	0.206	1290	1713.81	-423.81	24.73%	179616	912980
16	15	0.330	0.279	2385	1974.36	410.64	20.80%	168629	19460
17	16	0.308	0.254	2730	2428.66	301.34	12.41%	90806	234740
18	17	0.311	0.258	1740	2114.07	-374.07	17.69%	139927	255530
19	18	0.378	0.330	2580	1693.97	886.03	52.30%	785043	111890
20	19	0.304	0.251	3030	2447.02	582.98	23.82%	339868	615440
21	20	0.325	0.273	2535	2127.96	407.04	19.13%	165679	83810
22	21	0.312	0.259	2490	2569.12	-79.12	3.08%	6260	59780
23	22	0.313	0.260	1065	2083.69	-1018.69	48.89%	1037734	1393580
24	23	0.315	0.263	2595	2310.12	284.88	12.33%	81155	122150
25	24	0.330	0.278	2445	2021.80	423.20	20.93%	179095	39800
26	25	0.314	0.261	1680	2152.95	-472.95	21.97%	223678	319790
27	26	0.295	0.240	1650	1860.97	-210.97	11.34%	44509	354620
28	27	0.333	0.281	2790	2167.85	622.15	28.70%	387065	296480
29	28	0.293	0.239	1680	1739.55	-59.55	3.42%	3547	319790
30	29	0.296	0.242	2790	2665.60	124.40	4.67%	15475	296480
total								8632452	10210568
						Model 3	Out-of-sample R^2:		0.155

Appendix B (Case Information Used for Testing ADOPT)

Case #	Start	End	Total Min	Room
1	9:15	12:00	165	1
2	12:00	13:30	90	1
3	13:30	16:00	150	1
4	10:30	15:00	270	3
5	7:30	9:15	105	4
6	12:00	16:00	240	4
7	7:30	10:30	180	5
8	10:30	11:30	60	5
9	11:30	13:00	90	5
10	16:00	17:00	60	5
11	7:30	9:45	135	6
12	9:45	12:15	150	6
13	7:30	12:00	270	8
14	7:30	10:00	150	9
15	10:00	12:00	120	9
16	12:00	16:30	270	9
17	7:30	9:45	135	10
18	9:45	12:30	165	10
19	12:30	13:45	75	10
20	13:45	16:30	165	10
21	7:30	10:30	180	11
22	10:30	13:30	180	11
23	13:30	16:30	180	11
24	7:30	10:30	180	12
25	10:30	13:15	165	12
26	9:30	11:00	90	14
27	13:00	14:00	60	14
28	14:00	15:00	60	14
29	15:00	16:00	60	14
30	16:00	17:00	60	14
31	13:00	15:30	150	15
32	15:30	17:00	90	15
33	7:30	10:00	150	16

Case #	Start	End	Total Min	Room
34	10:00	11:45	105	16
35	7:30	10:00	150	17
36	10:00	16:30	390	17
37	7:30	10:15	165	19
38	10:15	13:15	180	19
39	13:15	16:30	195	19
40	7:30	9:30	120	20
41	9:30	11:30	120	20
42	11:30	13:30	120	20
43	7:30	10:30	180	21
44	10:30	13:15	165	21
45	13:15	17:00	225	21
46	8:00	9:15	75	23
47	9:15	10:30	75	23
48	10:30	12:00	90	23
49	12:00	13:00	60	23
50	8:00	10:00	120	24
51	14:00	16:00	120	24
52	8:00	11:00	180	25
53	11:00	14:00	180	25
54	8:00	9:45	105	26
55	10:30	13:30	180	26
56	13:30	17:00	210	26
57	8:00	10:45	165	27
58	10:45	12:15	90	27
59	12:15	14:00	105	27
60	14:00	15:45	105	27
61	15:45	17:00	75	27
62	8:00	9:45	105	31
63	8:00	12:15	255	33
64	12:15	15:45	210	33
65	8:00	11:00	180	34
66	11:00	14:00	180	34

Case #	Start	End	Total Min	Room
67	14:00	17:00	180	34
68	8:00	9:00	60	35
69	10:00	11:15	75	35
70	14:15	15:30	75	37
71	16:00	17:00	60	37
72	12:00	14:30	150	38
73	15:15	16:15	60	38
74	16:15	17:00	45	38
75	8:00	10:00	120	40
76	10:00	12:00	120	40
77	12:00	14:00	120	40
78	14:00	15:45	105	40
79	13:30	17:00	210	42
80	8:00	10:45	165	43
81	10:45	12:15	90	43
82	12:15	15:15	180	43
83	15:15	16:45	90	43
84	8:00	10:00	120	44
85	10:00	11:30	90	44
86	11:30	13:00	90	44
87	13:00	15:30	150	44
88	14:00	15:15	75	45
89	15:15	16:45	90	45
90	9:30	13:00	210	46
91	9:30	15:00	330	47
92	13:30	15:45	135	48
93	15:45	17:00	75	48
94	9:30	13:30	240	50
95	13:30	15:00	90	50
96	9:30	11:15	105	51
97	11:15	13:15	120	51
98	9:30	13:45	255	52
99	9:30	11:30	120	53

Case #	Start	End	Total Min	Room
100	9:30	16:30	420	54
101	9:30	12:45	195	55
102	12:45	17:00	255	55
103	9:30	11:15	105	62
104	11:15	12:45	90	62
105	12:45	16:15	210	62
106	9:30	10:45	75	64
107	10:45	12:15	90	64
108	12:15	13:45	90	64
109	14:00	15:45	105	65
110	7:30	9:00	90	67
111	9:00	10:45	105	67
112	15:00	17:00	120	67
113	7:30	11:15	225	68
114	7:30	10:00	150	69
115	12:00	14:30	150	71
116	14:30	17:00	150	71
117	7:30	12:00	270	74
118	7:30	8:45	75	75
119	9:00	10:30	90	75
120	10:30	12:00	90	75
121	7:30	11:00	210	76
122	11:00	12:45	105	76
123	12:45	14:15	90	76
124	14:15	17:00	165	76
125	7:30	10:30	180	77
126	10:30	13:15	165	77
127	13:15	16:15	180	77
128	7:30	9:15	105	78
129	7:30	9:30	120	80
130	9:30	10:30	60	80
131	10:30	11:30	60	80
132	11:30	12:30	60	80

Case #	Start	End	Total Min	Room
133	13:00	14:00	60	80
134	14:00	15:00	60	80
135	15:00	16:00	60	80
136	7:30	8:30	60	81
137	8:30	9:30	60	81
138	9:30	10:30	60	81
139	10:30	11:30	60	81
140	11:30	12:30	60	81
141	12:30	13:30	60	81
142	7:30	13:00	330	82
143	7:30	10:00	150	83
144	10:00	12:30	150	83
145	12:30	14:00	90	83
146	15:45	17:00	75	83
147	7:30	9:00	90	84
148	9:00	11:30	150	84
149	12:00	13:00	60	84
150	7:30	9:00	90	87
151	9:00	10:30	90	87
152	10:30	13:15	165	87
153	13:15	15:45	150	87
154	13:00	14:45	105	89
155	14:45	17:00	135	89
156	7:30	12:00	270	90
157	12:00	13:15	75	90
158	13:15	14:30	75	90
159	7:30	8:45	75	91
160	8:45	10:00	75	91
161	10:00	11:30	90	91
162	7:30	9:45	135	92
163	9:45	12:15	150	92
164	12:15	15:45	210	92
165	15:45	17:00	75	92

Case #	Start	End	Total Min	Room
166	7:30	9:00	90	94
167	9:00	10:30	90	94
168	10:30	12:00	90	94
169	12:00	13:30	90	94
170	13:30	15:00	90	94
171	7:30	8:30	60	95
172	8:30	9:30	60	95
173	9:30	10:45	75	95
174	7:30	12:00	270	96
175	12:00	17:00	300	96
176	7:30	11:15	225	97
177	12:00	17:00	300	97
178	7:30	12:45	315	98
179	12:45	14:45	120	98
180	14:45	17:00	135	98
181	7:30	12:00	270	99
182	13:00	14:00	60	99
183	14:00	15:30	90	99
184	10:00	11:15	75	101
185	7:30	9:30	120	102
186	9:30	11:00	90	102
187	11:00	12:30	90	102
188	7:30	9:15	105	104
189	12:30	13:45	75	104
190	14:30	16:00	90	104
191	7:30	10:30	180	105
192	10:30	12:00	90	105
193	7:30	9:15	105	107
194	9:15	10:45	90	107
195	7:30	9:30	120	108
196	13:30	14:45	75	109
197	15:45	17:00	75	109