

OPTIMIZING OPERATING ROOM SCHEDULING CONSIDERING INSTRUMENT
STERILIZATION PROCESSING

by
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DEDICATION

To my parents, Don and Cheryl Harris. Words cannot express how grateful I am for your love and support. I can only hope to live by the example you have set for me.

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COMMONLY USED ACRONYMS AND MODEL NOTATION

Acronym	Definition
BAMQ	Block Assignment Model Quadratic
BAMLGPD	Block Assignment Model Linear Goal Programming Deviation
BHDH	Bozeman Health Deaconess Hospital
CV	Coefficient of Variation
DES	Discrete Event Simulation
PHU	Preoperative Holding Unit
ICU	Intensive Care Unit
MIP	Mixed Integer Programming
OR	Operating Room
PACU	Post Anesthesia Care Unit
SPD	Sterile Processing Department
TOM	Tray Optimization Model
TOP	Tray Optimization Problem

Chapter 4 — BAMQ Notation and Definitions

$\bar{A}_i$	Average total time (minutes) for SPD staff to complete manual assembly of surgical group i 's daily caseload
a_s	Weight given to SPD objective term (between 0 and 1)
C_i	Average total time (minutes) for SPD staff to complete manual processing steps of surgical group i 's daily caseload
D_i	Maximum number of blocks surgical group i may have in a single block time
P_{ijk}	Preferences for surgical group i ($i = 1, 2, \dots, I$) to have OR j ($j = 1, 2, \dots, J$) during block time k ($k = 1, 2, \dots, K$)

$\bar{R}_i$	Average total time (minutes) for SPD staff to complete manual rinsing of surgical group i's daily caseload
SCV	Scaled Caseload Coefficient of Variation
$S_{ii'}$	Cost to the SPD of surgical groups i and i' having a block scheduled during the same time. Four different methods for calculating $S_{ii'}$ were examined
x_{ijk}	$\begin{cases} 1 & \text{if surgical group } i \text{ is assigned to OR } j \text{ during block time } k \\ 0 & \text{otherwise} \end{cases}$
W_i	Total number of blocks each group is allocated during the planning horizon

Chapter 4 — BAMLGPD Notation and Definitions

	BAMLGPD has the same notation and definitions as BAMQ, with the following additions
s_k^-	Amount the total daily caseload on day k is under the average total daily caseload
s_k^+	Amount the total daily caseload on day k is over the average total daily caseload

Chapter 4 — 2BAMLGPD Notation and Definitions

2BAMLGPD has the same notation and definitions as BAMLGPD, with the exception of the decision variables for the two phases:

x_{ik} (Phase 1)	Number of ORs surgical group i is assigned during block time k
y_{ijk} (Phase 2)	$\begin{cases} 1 & \text{if surgical group is assigned to OR } j \text{ during block time } k \\ 0 & \text{otherwise} \end{cases}$

Chapter 5 — TOM Notation and Definitions

A_{ip}	Desired amount of instrument i for procedure p
b_{it}	Quantity of reusable instrument i assigned to tray t
C_t	Desired weight capacity of tray t (in pounds)
MC_t	Maximum factor by which tray t can exceed its desired weight capacity
MO	Maximum overage amount of instrument i for procedure p
MU	Maximum underage amount of instrument i for procedure p

N_p	Annual frequency of procedure p
PA_{ip}	Penalty for not having the desired amount of instrument i for procedure p (per item)
PC_t	Penalty for tray t exceeding its desired weight capacity (per pound)
$s1_t^+$	Amount that tray t exceeds its desired weight limit
$s1_t^-$	Amount that tray t is under its desired weight limit
$s2_{ip}^+$	Quantity of instrument i for procedure p that is above the desired amount A_{ip}
$s2_{ip}^-$	Quantity of instrument i for procedure p that is below the desired amount A_{ip}
S_i	Total inventory amount of instrument i
U_{ip}	Expected non-use percentage of instrument i for procedure p (0 – 1)
W_i	Weight of item i (in pounds)
W_t	Weight of tray t (in pounds)
y_{tp}	$\begin{cases} 1 & \text{if tray t is used for procedure p} \\ 0 & \text{otherwise} \end{cases}$

ABSTRACT

The United States healthcare system represents approximately 18% of the nation's GDP and its numerous challenges continue to receive significant attention from researchers. Within healthcare, operating rooms (ORs) often represent the largest source of revenue and costs in a hospital. Consequently, OR surgical scheduling strategies have been thoroughly examined from a wide variety of performance measures such as overtime, patient waiting time, and utilization rates. ORs are a complex system, and researchers have begun to consider the upstream and downstream resources involved in the surgical process such as the Post Anesthesia Care Unit, Intensive Care Unit, and bed availability. However, two factors that have only begun to be examined are the sterilization process of OR instrumentation and the assignment of instruments into trays and preference cards, either by surgical procedure or individual surgeon preference. Using both collected and historical data, this research 1) examined and improved how the block schedule of an OR suite affected the Sterilization Processing Department (SPD) and 2) examined and improved preference cards for surgical cases. A series of mathematical models optimized surgical block schedules while considering the impact on the SPD and a goal programming model was developed for the tray optimization problem. A comprehensive simulation model of the OR suite and SPD tested the output of the mathematical models. The simulation results confirmed block scheduling does affect SPD performance. A linear goal programming formulation that smoothed SPD workload across block times was the most effective type of model to optimize block scheduling. A goal programming tray optimization model improved expected instrument utilization rates. For practical applications, this research suggests reducing SPD staff turnover is a more effective method for improving SPD performance than rearranging the OR block schedule. This research is among the first of its kind to consider SPD workload as an objective in OR block scheduling models, to consider expected instrument non-usage rates in the tray optimization problem, and to develop a comprehensive simulation model of an OR suite and its SPD to test the results of mathematical models.

CHAPTER ONE

INTRODUCTION

Problem Description

The United States healthcare system represents approximately 18% of the nation's GDP and its numerous challenges continue to receive significant attention from researchers [41]. Within healthcare, operating rooms (ORs) often represent the largest source of revenue and costs in a hospital [57, 66, 135]. Consequently, OR surgical scheduling strategies have been thoroughly examined from a wide variety of performance measures such as overtime, patient waiting time, and utilization rates [36, 134, 159]. Additionally, supply chain costs often incur up to 40% of a hospital's budget, with 61% of that coming from perioperative services [46]. As a result, researchers are also examining OR materials management [187].

ORs are a complex system, and researchers have begun to consider the upstream and downstream resources involved in the surgical process such as the Post Anesthesia Care Unit (PACU), Intensive Care Unit (ICU), and bed availability [36, 159]. However, two factors that have only begun to be examined are the sterilization process of OR instrumentation [28, 159] and the assignment of instruments into trays and preference cards, either by surgical procedure or individual surgeon preference. Examining how block schedules can affect the sterilization processing department (SPD) workload has not been examined.

Despite the scant attention they receive, the SPD and preference cards can negatively impact the OR system. Inefficient preference cards lead to low instrument utilization rates during procedures. However, these unused instruments still need to go through the entire sterilization process again, which consumes valuable time and resources. Several studies have demonstrated more efficient preference cards have the potential to save tens of thousands, if not millions, in annual costs

[11, 17, 58, 59, 61, 141, 169, 195, 215]. Furthermore, inefficient preference cards result in trays being over the maximum allowable weight, which adversely affects the staff that transport them. It also leads to instruments stacking on top of one another on trays in the OR due to lack of space.

Overworked SPD staff could make errors when sterilizing instruments, which presents significant risk to patient safety. The SPD plays a critical role in helping prevent surgical site infections, which are quite costly. Urban [177] provides a review of several studies that quantify surgical site infection costs. All told, these infections can consume up to \$10 billion in annual direct and indirect medical costs [177]. Furthermore, an unnecessarily long sterilization process can become a bottleneck in OR throughput, creating delays in subsequent surgery starts. Perhaps Swanson [173], in the article “Shifting the sterile processing department paradigm: a mandate for change”, describes this challenge best:

“Until recent years, some health care administrators held the private and rarely expressed belief that staff members in the sterile processing department (SPD)...were “nothing more than glorified dish washers.” ... It is generally understood that SPDs have a significant role in supporting the surgical department, which typically is the dominant revenue generating department in the hospital. The importance of the SPD, however, can be overlooked because it does not produce its own revenue. When considering the role the SPD plays in supporting the emergency department, intensive care unit, and labor and delivery, however, the volume of resources passing through the SPD is staggering.”

Thesis Outline

The goal of this research was to 1) examine and improve how block scheduling for an OR suite affects the SPD and 2) examine and improve preference cards for surgical cases.

There are two hypotheses driving this research:

Sterilization department hypothesis (H_1): Despite its critical role in the OR surgery process, researchers and practitioners have not accounted for the SPD when developing long term scheduling strategies as they have for other upstream and downstream resources [28, 159]. Consequently, an important dynamic is missing in the existing mathematical

scheduling models and strategies. A block assignment model that considers SPD workload can improve SPD performance. A comprehensive simulation model incorporating the SPD can test the block assignment model results.

Preference card hypothesis (H₂): OR preference cards, which designate what instruments are in what trays and what trays are assigned to a given surgical procedure, are often inefficient. This results in a substantial percentage of instruments and trays going unused during procedures. The unnecessarily high number of instruments going through the SPD decreases the daily SPD throughput, which can cause delays in subsequent OR surgery start times or affect how surgeries are scheduled. A goal programming model can improve preference cards. This will result in better SPD throughput. A comprehensive simulation model can test the goal programming model results.

This research study had two primary objectives. **The first objective was to develop a mathematical model that allocated surgical blocks to multiple surgical groups.** This model included the number and types of blocks available for scheduling, the number of surgical groups requiring a block and their preferences for different block times, and the impact on the SPD of scheduling different surgical groups during the same block time.

The second research objective was to build upon the emerging research area of mathematical models that assign instruments to trays and trays to preference cards based upon current inventory, surgical demand, surgeon preference, and human factors elements. The outcome of this phase was a goal programming model that optimized preference cards for select procedures.

A simulation model of the OR suite that included the SPD was developed to validate the results of the mathematical models. This entailed observing the SPD and recording times for the steps involved to calculate probability distributions for the stochastic steps in the process. The

outcome of this step was a detailed simulation model that measured the effectiveness of applying the mathematical models' results to the OR system.

This research study is organized as follows. Chapter two is the literature review, with the primary focus being on OR scheduling and how this study fills research gaps. The OR scheduling portion of the literature review is in itself a research contribution. Chapter three outlines the research methodology. Chapter four discusses the OR block assignment model. Chapter five reviews the preference card model. Chapter six covers the comprehensive simulation model. Chapter seven summarizes the research. Figure 1 displays the research overview and how the objectives fit into the research outline.

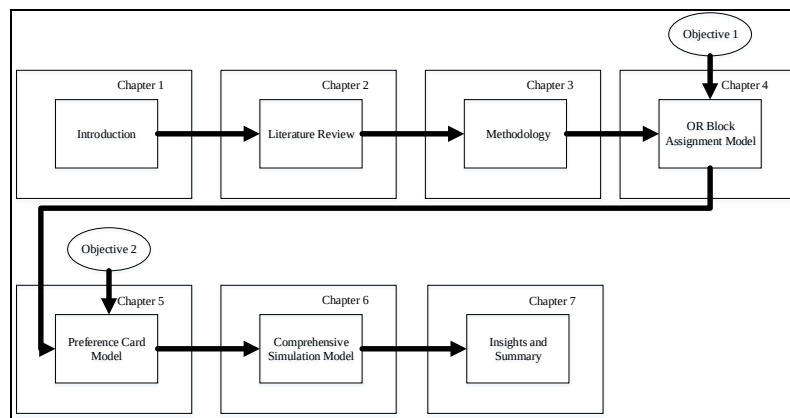


Figure 1: Research Overview

CHAPTER TWO

LITERATURE REVIEW

Introduction

The nation's healthcare system is incredibly complex and expensive. Thus, there is a plethora of opportunities for researchers from a variety of fields to improve healthcare systems. Researchers have examined various aspects of a hospital system, such as an oncology clinic [85] or emergency department [92, 121, 205, 206]. Many healthcare researchers have shown that the OR represents the single largest source of revenues and costs within a hospital [36, 49, 115]. Consequently, researchers have devoted considerable attention to the OR scheduling problem in the 21st century. The number of published technical OR scheduling articles has consistently grown since 2000 [48, 159]. This fact does not imply researchers have become repetitive. Rather, it reflects the plethora of ways to examine the problem through different perspectives and hospital environments across the world.

OR scheduling literature reviews are useful for several reasons. First, literature reviews classify articles according to several categories, which helps researchers find articles similar to their own research. This can save researchers' valuable time combing through databases to ensure the contribution from their upcoming research is unique. Second, literature reviews identify areas for future research. This can help guide the direction of research in a field. Third, literature reviews provide a common structure and terminology for a field that spans the entire world. Establishing common terminology to use in articles helps reader comprehension, especially considering the diversity of researchers' native languages. Finally, literature reviews can identify common shortcomings across a field, which can help improve the quality of future works.

Cardoen, Demeulemeester, and Beliën [36] established a useful classification system that served as a guide for two recent literature reviews [48, 159]. Collectively, those three reviews cover OR scheduling papers from 2000-2014, with a focus on technical articles. This literature review uses a similar classification system and covers technical articles from 2015 to early 2018. Additionally, it includes a geographic map that specifies the location and frequency of recent OR scheduling research. This map can help connect researchers and encourage collaboration.

The search methodology for this literature review was similar to Samudra et al. [159], with Web of Science and PubMed the primary databases and English the only language considered. Search terms included combining the following words: surgery, operating room, case, scheduling, sequencing, and planning. The list of references for selected articles was also searched. Articles were considered technical if they included some sort of mathematical or simulation modeling that made or guided OR scheduling decisions. Articles were considered managerial if they lacked these things and focused on empirical studies, determining surgical durations, or discussing common practices, among others. In all, 113 technical articles were found from 2015 through April 2018. Forty-one articles were published in 2015, 37 in 2016, 31 in 2017, and 4 in 2018, though this number is likely to increase substantially as the year progresses. In fact, an initial search in February 2019 yielded 21 additional articles [7, 8, 14, 25, 72, 80, 89, 95, 98, 100, 113, 118, 124, 129, 137, 149, 161, 178, 190, 194, 208]. Once the final search is complete, it is expected that the number of articles in 2018 will continue along the increasing trend. The publication numbers continue the gradual increase in articles per year from Samudra et al. [159], in which the number of articles per year peaked at 33 in 2014. While the timespan is relatively short, the increasing number of articles published per year necessitates an updated literature review that informs researchers on current trends.

Organization of the Review

This review includes the six categories found in [36, 48, 159]. They are: *patient type*, *performance measures*, *decisions delineation*, *techniques*, *uncertainty*, and *testing and applicability*. A seventh category, *upstream/downstream resources*, was introduced by Samudra et al. [159] and will continue in this literature review. For consistency, this review maintains the same order of categories as the most recent review [159]. That will be followed a new category, geographic location. For each category, a brief description of the field will be followed by tables summarizing how the 113 technical articles fit into the field. Selected articles are highlighted to illustrate examples, and any trends that emerge are compared to trends from previous literature reviews. Each section includes opportunities for future research. The sections conclude by stating if this research study help fill the identified research gaps. Finally, the review finishes with a comprehensive summary of the findings across all categories and how the research addresses some of the areas where future research is needed.

Patient Type

The two primary patient types are elective and non-elective. Elective surgeries are planned before the day of surgery, whereas non-elective surgeries are unknown and must occur shortly after the patient arrives to the hospital (usually at the Emergency Department). Patients undergoing elective inpatient surgery stay at least one night in the hospital. Elective outpatients discharge the same day of surgery. Often, researchers will not distinguish if elective cases are inpatient or outpatient because those details may not apply to their model, in which case they are classified as general elective surgeries.

Non-elective surgeries are often classified as urgent or emergent, however, the exact definitions can vary from country to country. Generally, emergent surgeries require the case to start

within an hour of the patient arriving, whereas urgent surgeries have a longer window but usually no longer than one day. Like elective surgeries, researchers often do not distinguish between urgent or emergent non-elective surgeries, in which case they are classified as general non-elective. Table 1 summarizes the articles' classification according to patient type.

As table 1 illustrates, virtually all (110/113) of the articles consider elective cases. This continues the same trend from previous literature reviews [36, 48, 159]. Samudra et al. [159] noted that while outpatient surgeries are becoming more frequent in recent years, the number of published articles that consider outpatient cases have not. Table 1 illustrates this trend has remained over the last few years. The percentage of articles incorporating outpatient cases hovered between 15% from 2004-2014 [159] and dropped slightly to 12% from 2015 - present.

Table 1: Patient Type

Elective Surgery	
<i>Inpatient</i>	[1, 15, 21, 26, 27, 64, 65, 72, 79, 105, 117, 138, 145, 151, 156, 160, 162, 180, 184, 185, 189, 191, 202, 209]
<i>Outpatient</i>	[65, 70, 72, 105, 117, 130, 145, 151, 160, 162, 184, 185, 209]
<i>General</i>	[2, 5, 10, 16, 19, 20, 24, 28, 32-34, 38, 39, 50, 54, 56, 62, 63, 67, 69, 71, 73, 74, 76-78, 81-83, 87, 88, 90, 91, 94, 96, 101, 102, 104, 106, 107, 110-112, 114, 116, 119, 120, 122, 123, 125-128, 131, 134, 136, 142, 143, 146, 147, 154, 155, 157, 158, 166-168, 171, 175, 186, 188, 192, 193, 197-201, 204, 207, 211-214]
Non-Elective Surgery	
<i>Urgent</i>	[33, 68, 74, 104, 151, 210]
<i>Emergent</i>	[1, 9, 33, 68, 94, 143, 151, 175, 188, 207, 210]
<i>General</i>	[34, 62, 63, 77, 134, 158, 209, 210]
<i>Weekend</i>	[65]

Considering the dynamic between outpatient and inpatient presents interesting challenges for researchers. Fügener et al. [65] considered how a stochastic mix of inpatient and outpatient surgeries affect downstream resources. The authors used mixed integer programming (MIP) to determine the

optimal block schedule for surgical specialties and extended the model to include weekend non-elective cases.

Non-elective cases present many challenges to OR managers because of the inherent uncertainty in their arrival rate. There are two primary ways to plan for non-elective cases. First, OR managers may allocate specific ORs solely for non-elective cases. Second, OR managers may plan for a certain amount of slack time throughout the OR suite to allow enough time to fit in non-elective cases as they arrive. The first method ensures non-elective cases can be addressed promptly but can cause a high amount of OR idle time which adversely affects hospitals' costs. Conversely, the second technique yields better OR utilization at the expense of service level. Determining the optimal break-in time for non-elective surgeries for the second method is an interesting challenge for OR managers, and Wang et al. [188] examined this problem in detail. Zenteno et al. [210] is one of the few articles that only considered outpatient cases. The authors used discrete event simulation to examine how centrally managing non-elective "open blocks" can reduce the percentage of patients who received surgery within the prescribed wait time.

There is a debate as to which non-elective planning method is better. Wullink et al. [196] used discrete event simulation to show that allocating non-elective capacity across multiple ORs is better than a designated non-elective OR when waiting time, staff overtime, and OR utilization are used as the performance metrics. However, van Veen-Berkx et al. [182] conducted an empirical study which showed a dedicated non-elective OR improved the performance in terms of OR utilization, overtime, and case cancellations. The preferred method may depend on the hospital setting, as Zenteno et al. [210] suggested allocating capacity across multiple ORs is better for settings with relatively low non-elective case volume.

As table 1 illustrates, non-elective cases are only considered in approximately 18% of articles, which is a decrease from 27% for 2004-2014 [159]. In many instances, authors simply assume a dedicated OR for non-elective cases. This assumption simplifies the model by removing a

major source of uncertainty. However, unless this assumption applies to a specific setting in which researchers are applying their model, the applicability of their work decreases.

Thus, future research for patient types lies in several areas. First, more consideration of outpatient cases is needed. Outpatient case research was recommended by Samudra et al. [159] but an increase in the percentage of outpatient cases in articles has not occurred. Second, examining dedicated ORs for non-elective surgeries versus allocating capacity across multiple ORs is an open problem. Many OR managers face this problem and more information about what methods may be better for certain settings is needed. Finally, more articles that consider non-elective cases are needed. While it may not apply to hospitals with a dedicated OR for non-elective surgeries, there can certainly be a higher percentage of articles considering the challenge than the current proportion of 23%.

This research study considered both elective and non-elective cases. The hospital at the research location does not have a dedicated OR for non-elective surgeries, making non-elective case consideration critical to any scheduling strategy it implements.

Performance Measures

Performance measures reflect the needs of different stakeholders in the OR system. Patients are primarily concerned with cancellations and wait time [159]. Wait time can be expressed in terms of the number of days between referral and surgery date or the waiting time on the day of surgery. Hospital management is more concerned with performance measures that affect bottom line such as utilization, overtime, idle time, and throughput [159]. Hospital staff is usually concerned about overtime, shift assignments (both in time and colleagues they are working with during the shift), and block time allocation.

Selection of performance measures plays a critical role in driving model solution direction. Models focusing purely on patient-centered metrics will decrease wait times but may increase OR

idle time and lower hospital revenue [48]. Conversely, hospital management metrics may increase profitability at the expense of patient wait times, cancellations, and dissatisfied OR staff [48].

Researchers often include multiple performance measure to balance competing priorities, either through a weighted sum objective formulation or financially quantifying multiple measures into a comprehensive bottom line [159].

Table 2 displays performance measures by article. An additional caveat in this review from Samudra et al. [159] is that patient wait time is now divided into two separate categories. *Waiting time-number of days* refers to the number of days a patient spends on a wait list prior to the day of their surgery. *Waiting time-within day* refers to the time a patient spends waiting on the day of their surgery, usually expressed by the total time between OR opening and surgery start time or scheduled surgery start time and actual start time. Researchers often distinguish between different patient categories on a wait list by giving more weight to more urgent patients. Samudra et al. [158] focus on the due dates surgeons assign to patients. The authors used discrete event simulation to test how different scheduling strategies affected patient waiting time and the percentage of patients who received surgery after their due date.

Financial performance measures often involve quantifying conflicting metrics. Xiao et al. [201] developed a stochastic programming formulation with the objective of minimizing the financial costs of overtime and case cancellations. More overtime allowed for lower total cancellation costs but higher overtime costs that increased with the magnitude of the overtime duration. The authors found that human resource unavailability played a significant role in solution quality when applied to large urban hospitals in China.

Selection of performance metrics from 2015 onward mark a change from previous literature reviews. Figure 2 summarizes the change in proportion in popular performance metrics from the most recent review [159], which covers articles published from 2004-2014. The majority of common performance metrics see an increase in percentage used, with overtime decreasing. However, models

often implicitly incorporate overtime into financial calculations. Additionally, Samudra et al. [159] defined overtime to cover both overtime and overutilization, though the authors noted that the two terms do not mean the same concept, which suggests the actual decrease in articles using overtime is not as significant. The increase in performance metrics shows researchers are increasingly using multiple performance metrics in their models.

Table 2: Performance Measures

Waiting Time	
<i>Patient-within day</i>	[20, 33, 62, 74, 83, 128, 134, 157, 160, 162, 188, 210]
<i>Patient-number of days</i>	[5, 15, 16, 24, 27, 54, 56, 63, 69, 70, 73, 82, 90, 105, 106, 112, 116, 117, 120, 122, 123, 125, 130, 131, 143, 146, 151, 154, 158, 186, 193, 204, 210, 213]
<i>Surgeon</i>	[67, 128, 212]
Levelling	
<i>OR</i>	[101, 128]
<i>Recovery Bed</i>	[27, 65, 105, 142, 156, 186, 209]
<i>Staff</i>	[26, 87, 197]
Utilization	
<i>OR</i>	[2, 5, 16, 20, 24, 32, 38, 39, 56, 65, 69, 71, 76, 81, 83, 88, 94, 96, 101, 105, 111, 119, 125, 138, 157, 166-168, 186]
<i>Recovery Bed</i>	[16, 105, 156]
<i>Nurse</i>	[71, 107]
OR Overtime	[5, 10, 16, 21, 33, 34, 56, 62, 67-70, 73, 77, 78, 90, 94, 111, 112, 126, 131, 138, 143, 145, 146, 155, 157, 197, 201, 207, 212]
OR Idle Time	[2, 10, 32, 39, 67, 114, 123, 212, 214]
Throughput/Number of Surgeries Performed	[9, 19, 20, 24, 38, 69, 96, 106, 117, 119, 120, 123, 125, 147, 171, 180, 185, 186, 202, 204, 210]
Makespan	[77, 91, 102, 110, 126, 151, 157, 162, 188, 189, 191, 192, 197, 199, 200, 211]
Preferences	[10, 50, 87, 126, 127, 142, 151, 180, 186]
Financial	[2, 15, 21, 27, 34, 62, 64, 67, 68, 104, 111, 131, 136, 138, 145-147, 154, 155, 166, 175, 184, 189, 193, 198, 201, 207, 213]
Deferral/postponement	[70, 73, 77, 88, 94, 101, 143, 156, 201]
Other	[1, 2, 21, 27, 28, 50, 65, 68, 72, 73, 77, 79, 88, 91, 112, 126, 127, 130, 131, 136, 145, 158, 160, 204, 214]

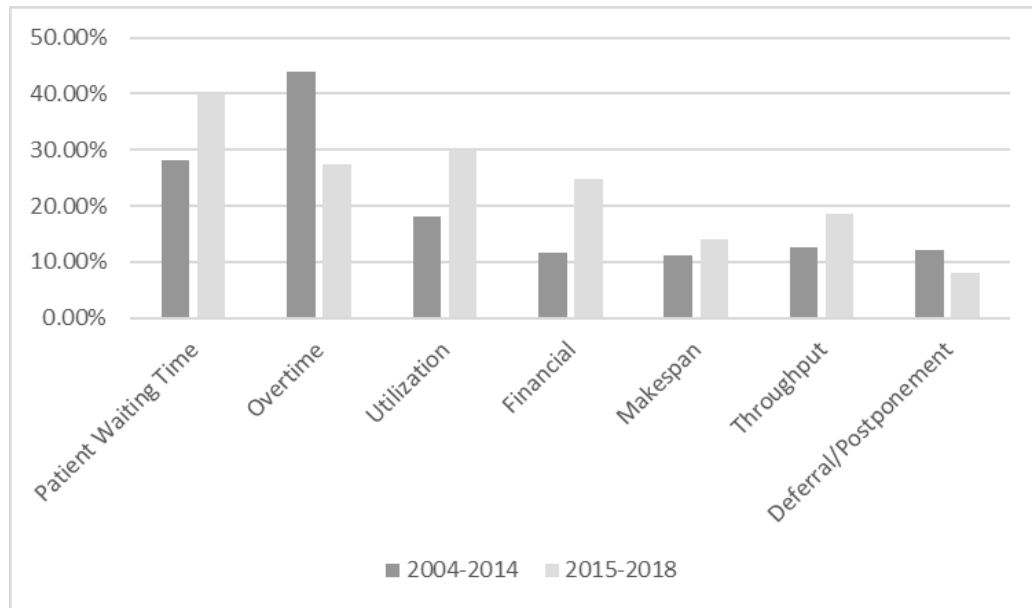


Figure 2: Change in Performance Metric Usage

In addition to common performance measures, researchers continue to develop many innovative performance measures that are applicable to challenges at their local hospital setting. The OR is not always the bottleneck in the perioperative process. Consequently, performance measures often include upstream or downstream resources where bottlenecks occur. For example, Zhu et al. [214] employed a MIP model to small rural hospitals in China that had a single OR and PACU room to minimize both OR and PACU idle time considering uncertain patient recovery times. The authors found that sequencing patients with longer expected recovery times earlier helped reduce total idle time in the system. A German hospital was experiencing high variation in the ICU and recovery bed demand throughout the week, which was causing significant stress on staff [65]. The authors examined how best to allocate surgical blocks to level the ICU, recovery bed ward, and OR throughout the week. Private healthcare facilities in Tunisia struggled with efficient use of recovery beds. Researchers formulated a mathematical model that reduced the average patient length of stay and number of overnight stays, which decreased the stress on the recovery bed ward [72]. Finally,

Gerami and Saidi-Mehrabad [68] considered “humanitarian” factors such as justice, individual freedom, and medical ethics when modeling reactive scheduling for emergent and urgent patients.

The most recent literature review identified behavioral factors such as staff satisfaction as an area for future research [159]. The area is starting to gain traction. Van Huele and Vanhoucke [180] incorporated surgeon preferences for several factors such as type of surgeries and working hours per week by utilizing soft constraints in which the deviation from the constraints penalized the objective function. Monteiro, Meskens, and Wang [126] considered the conflicting behavior objectives of teamwork quality and nurse skills. On one hand, nurses preferred to work with certain staff for certain surgeries, which was good for short term performance. However, over the long term it was important for nurses to participate in different surgeries with different staff to improve their overall skill set. The authors included these conflicting behavior objectives into a larger multi-objective formulation that included makespan and overtime cost.

Incorporating staff satisfaction is not always feasible for researchers because it requires working directly with hospital staff [159]. Another common method of incorporating satisfaction into mathematical models is by attempting to level or decrease the workload. Workload is normally defined by patient-based characteristics such as the number and/or severity of patients seen by a particular staff at the hospital, bed occupancy, and balancing OR utilization [4, 35, 203]. However, much like the SPD in general, the workload of SPD staff has received little attention from researchers [28, 159, 163]. This research looked at reducing the number and weight of instrument trays within the SPD with the aim of decreasing the SPD staff’s workload.

Decision Delineation

Decision delineation describes the type of decision(s) the researcher or OR manager must make. In the literature, researchers often use several terms in describing this category. Three common terms corresponding to the timeline of the decision are: *case mix planning*, *master surgery*

planning, and *patient scheduling* [36]. Case mix planning refers to the long-term planning of patient volume and composition [36]. Master surgical planning (MSP) or master surgical scheduling (MSS) is a medium term iterative schedule that assigns blocks of time throughout a time period (usually a week) to surgical groups or specialties and is usually done on a quarterly or semi-annual basis [36]. Patient scheduling refers to the short-term scheduling of surgeries [36].

Within patient scheduling, advance scheduling refers to assigning a surgery date for a patient [159]. Allocation scheduling refers to the sequence or individual start times within a specific OR for a day [159]. However, these terms are often loosely defined and can mean different things in different articles [36, 159]. Additionally, there are three primary scheduling policies: *block*, *open*, and *modified block*. Block scheduling allocates designated times and ORs to specific surgeons or specialties, open utilizes a first come first serve system, and modified block is essentially block scheduling with unused time being given out in an open scheduling manner [153]. Open scheduling was more common in the 1960s and 1970s but block scheduling has become more popular because it better utilizes surgeon's time [31].

Cardoen, Demeulemeester, and Beliën [36] present a more comprehensive way to examine decision delineation based on the entity (discipline or surgical specialty, surgeon/clinic, and patient) and corresponding location or time related decision. Demeulemeester et al. and Samudra et al. [48, 159] continue the classification scheme and the same methodology is continued here. Additionally, this study's review provides data on planning horizon and scheduling methods. Table 3 displays decision delineation information.

Patient level decisions continue to receive most of the attention in articles. Often, authors incorporate multi-stage models that consider the date, room, and time a patient's surgery will occur. For example, Addis et al. [5] developed a linear program that assigned patients a date, time, and room for surgery in a block scheduling system. Additionally, the authors updated the schedule over a rolling horizon approach to reflect the stochastic patient waiting list.

Table 3: Decision Delineation

	Discipline Level	Surgeon Level	Patient Level	Other
Date	[1, 15, 27, 38, 64, 65, 69, 116, 127, 147, 171, 175, 185, 186, 202]	[10, 32, 38, 54, 69, 71, 79, 81, 87, 105, 112, 119, 120, 123, 125, 136, 138, 142, 147, 155, 156, 171, 180, 186, 209]	[2, 5, 10, 15, 16, 24, 26, 28, 32, 34, 39, 54, 56, 69-71, 73, 76, 77, 82, 88, 90, 94, 101, 106, 112, 117, 119, 122, 123, 125, 130, 131, 136, 138, 143, 146, 151, 154, 155, 158, 171, 180, 193, 204, 213]	[50, 71, 90, 123, 184, 185]
Time	[1, 15, 38, 64, 65, 69, 127, 147, 171, 175, 202, 210]	[10, 21, 38, 54, 69, 71, 72, 79, 81, 87, 104, 105, 111, 112, 119, 123, 126, 128, 136, 142, 147, 156, 171, 192, 198-200, 212]	[2, 5, 9, 10, 19-21, 24, 28, 32-34, 54, 56, 62, 67-69, 71-74, 76-78, 91, 96, 101, 102, 104, 106, 110-112, 114, 117, 119, 122, 123, 126, 128, 130, 131, 134, 136, 145, 151, 157, 160, 162, 166-168, 171, 180, 188, 189, 191-193, 197-201, 204, 207, 211, 213, 214]	[50, 71, 78, 83, 91, 107, 111, 123, 126, 130, 136, 145, 155, 167, 184, 192, 198-200]
Room	[1, 15, 27, 38, 64, 65, 69, 116, 147, 171, 175, 185, 186, 202, 210]	[10, 21, 38, 54, 69, 71, 72, 79, 81, 104, 105, 111, 112, 114, 119, 123, 125, 126, 128, 136, 142, 147, 155, 156, 171, 186, 192, 198-200, 209]	[2, 5, 9, 10, 15, 16, 19-21, 24, 32, 34, 39, 54, 56, 62, 67-74, 76, 77, 94, 101, 104, 106, 110-112, 114, 117, 119, 123, 125, 126, 128, 130, 131, 136, 143, 145, 151, 154, 155, 157, 158, 160, 162, 166-168, 171, 180, 191-193, 197-200, 204, 207, 213]	[50, 63, 71, 78, 83, 91, 107, 123, 126, 145, 167, 192, 198-200]
Other	[127, 184, 202]	[155, 186]	[21, 82, 88, 130, 154, 155, 160, 193, 197-199, 213]	[94, 107, 185]

Figure 3 denotes the change in proportion of decision delineation from the most recent literature review. Notably, the proportion of articles considering surgeon or discipline level decisions has increased, while patient-time and patient-room decisions have also increased. The increase is likely due to the growing number of articles that consider both discipline/surgeon and patient level

decisions, either simultaneously or in a two-stage process. Aringhieri et al. [15] developed a two-level metaheuristic to simultaneously address block assignment and advance scheduling. The authors assigned surgical specialties dates, rooms, and times for a weekly schedule and assigned patients a date and block for that surgery. Dios et al. [54] developed a decision support system (DSS) in Spain that assigned both surgeons and patients dates, rooms, and times under an open scheduling policy. The MIP model underlying the DSS minimized patient waiting time.

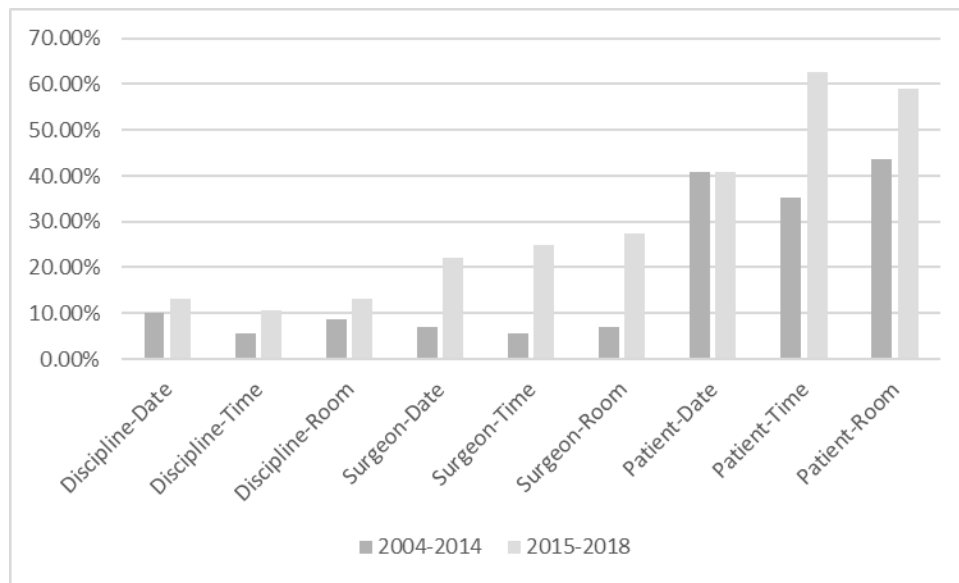


Figure 3: Change in Decision Type Usage

Authors continue to explore decisions outside of the traditional OR scheduling canon. Perhaps the most interesting decision in recent articles was Nemati et al. [130], who developed a MIP and algorithm to address a challenging problem. Access to ORs by patients living in the rural United States can be difficult since patients often need assistance with transportation to the hospital. The authors considered how to determine the best way to not only schedule patients for surgery, but also how to pick them up, drive them to the hospital, and then return them home after surgery. Essentially, the authors combined the OR scheduling problem with the vehicle routing problem.

Table 4 presents the breakdown for scheduling policy by articles. Block scheduling is more common than open (44% versus 35%). This research study assumed a block scheduling system because that was the methodology at the research location, Bozeman Health Deaconess Hospital (BHDH).

Table 4: Scheduling Policy Used

Block	[1, 2, 5, 9, 10, 15, 16, 20, 21, 24, 27, 38, 39, 50, 56, 62, 64, 65, 68, 69, 71, 79, 87, 90, 101, 102, 105, 112, 114, 116, 117, 120, 131, 134, 136, 138, 142, 143, 145, 147, 151, 154, 156, 158, 168, 175, 185, 186, 202, 204]
Open	[19, 26, 28, 32, 33, 54, 67, 70, 72, 74, 76, 77, 96, 111, 119, 123, 125, 126, 128, 130, 155, 157, 160, 166-168, 188, 189, 191-193, 198-201, 207, 211-214]
Modified Block	[81, 104, 125, 184, 209]
Unclear/Other	[63, 73, 82, 83, 88, 94, 106, 110, 122, 127, 146, 162, 180, 197, 210]

Table 5 presents the planning horizon of the articles. The planning horizon refers to the timespan over which the model makes unique decisions. For example, many articles that determine surgical block times for surgeons or specialties use 1-2 weeks for the planning horizon because the hospital wants to maintain the same weekly or bi-weekly block schedule. Longer term plans such as patient volume and composition usually span 6 months or more. Most attention is paid to the shorter-term horizons.

Table 5: Planning Horizon

Day	[9, 10, 20, 21, 33, 56, 62, 67, 68, 70, 72-74, 77, 78, 83, 91, 96, 102, 104, 107, 110, 111, 114, 122, 126, 128, 130, 134, 136, 145, 151, 157, 160, 162, 166-168, 188, 189, 191, 192, 197-201, 204, 207, 211-214]
1-2 Weeks	[2, 5, 10, 15, 16, 19, 24, 26, 28, 32, 38, 39, 50, 54, 56, 64, 65, 69-71, 73, 76, 77, 79, 82, 88, 90, 94, 101, 106, 112, 114, 116, 117, 119, 122, 123, 125, 127, 130, 131, 136, 142, 143, 146, 147, 151, 154-156, 158, 171, 180, 184, 185, 193, 202]
Month	[5, 16, 27, 39, 87, 90, 105, 112, 125, 175, 186]
2-5 Months	[1, 120, 138, 151]
6 Months or more	[54, 63, 81, 147, 184, 209, 210]

Researchers do not always explicitly state planning horizon and multi-stage models may consider multiple time spans. Gul, Denton, and Fowler [70] developed a multi-stage stochastic program that considers stochastic patient demand and surgery cancellations. The model made allocation decisions within each day and assigned surgeries a date over a 1 or 2-week planning horizon. Surgeries that could not be assigned within the given planning horizon were assigned a dummy date.

The primary opportunity for future research identified in Samudra et al. [159] for decision delineation was dynamic scheduling. Dynamic scheduling refers to when a patient is scheduled at the end of the initial consultation. Dynamic scheduling contrasts with static scheduling, in which the patient is placed on a waiting list and then the waiting list is processed all at once. Dynamic scheduling continues to be a promising area for future research. Additionally, authors should avoid ambiguous scheduling terms when discussing decision delineation. Authors could even state how their paper fits into the classification scheme developed by Cardoen et al. [36] and continued in the most recent literature reviews (some are even beginning to do this, such as [117]). Finally, authors can clearly state the planning horizon of their models.

Using the decision delineation classification, this research study focused on the surgeon/clinic – date/room decisions. The planning horizon was one week, which was the length of the iterative block schedule at BHDH.

Upstream/Downstream Units

Hospitals are complex systems composed of many interrelated departments. Consequently, many units outside the OR can play a critical role in the OR's performance [159]. Incorporating upstream and downstream units helps make models more realistic and applicable. However, complexity presents two challenges. First, the solution time of the models can increase significantly.

Second, outside units have their own set of stakeholders with competing priorities, which can make data collection and collaboration challenging from the researchers' perspective.

The most recent review found that despite the growing complexity of models from 2004-2014, the percentage of articles considering at least one upstream or downstream unit has stagnated around 50% [159]. Articles integrating the PACU started to see an increase from 2007 on, though articles that considered the ICU remained scarce [159]. Finally, the authors recommended future research include more upstream (pre-operative) units and more non-traditional units such as inventory management, reimbursements, and the SPD [159].

Articles from 2015 on continue similar trends, with some improvement in ICU and upstream units. Table 6 displays upstream and downstream units. The percentage of articles considering at least one upstream or downstream unit increased slightly to 54%.

Table 6: Upstream and Downstream Units

Isolated OR	[2, 5, 9, 10, 24, 32, 33, 38, 50, 54, 56, 62, 69-71, 74, 76, 81-83, 87, 90, 94, 96, 104, 106, 107, 110, 111, 114, 116, 117, 119, 122, 123, 125-127, 134, 136, 143, 145-147, 154, 155, 158, 160, 162, 166, 167, 171, 175, 184, 189, 191, 201, 210-212]
Recovery Bed	[15, 16, 19, 27, 39, 63-65, 72, 73, 79, 101, 105, 120, 138, 142, 151, 156, 157, 168, 180, 185, 186, 192, 202, 204, 207, 209, 213]
PACU	[1, 20, 21, 68, 77, 102, 128, 188, 193, 197-200, 209, 214]
ICU/PICU	[1, 26, 64, 65, 79, 88, 131, 142, 157, 213]
Pre-Surgery Bed/Activities	[19, 68, 72, 128, 188, 197-200]
Other	[19, 28, 78, 91, 112, 120, 130, 151]

Most articles still consider downstream units such as the PACU or recovery bed/ward. However, upstream units have started to receive more consideration. Xiang and Li [198] and Xiang, Lin, and Yim [199, 200] each modeled the surgery process as three distinct stages: the pre-operative holding unit, the OR, and PACU. The authors considered a finite number of bed and staff resources

at each stage and used ant colony optimization to solve a MIP that minimized the makespan [199, 200] or financial costs [198].

While OR equipment is not an upstream or downstream unit, researchers are starting to incorporate it as a constraint in their models. For example, Al-Refaie et al. 2017 and Haghi et al. 2017 had constraints that a case could only be performed in a particular OR if the equipment for that case was available in the OR [9, 73].

The ICU can be challenging for researchers to incorporate due to the inherent uncertainty surrounding its use. It is usually not known beforehand whether a patient will be admitted to the ICU after surgery. Furthermore, patients coming from areas outside of the OR may already occupy ICU beds. Consequently, models considering the ICU usually have stochastic elements in them. Fügener and Fügener et al. [64, 65] both considered a stochastic patient path and calculated the expected ICU patient demand to avoid exceeding its capacity.

Non-traditional units, though not as common as the traditional Preoperative Holding Unit (PHU), ICU, PACU, or recovery ward, can affect performance of the OR a hospital's bottom line. Future research for upstream and downstream units should explore non-traditional units such as the SPD, inventory management, and reimbursement departments. While pre-operative units and the ICU are starting to receive more attention, the proportion of articles considering them should increase in the coming years. Furthermore, authors should collectively strive to increase the percentage of articles that consider at least one upstream or downstream unit.

Beroule et al. [28] are among the first to consider the SPD, which cleans OR instruments and repackages them for future surgeries, into an OR scheduling model. The authors used particle swarm optimization to determine a surgery schedule that minimized the number of instrument boxes needed to complete all surgeries for a given week. Minimizing the number of boxes reduced total operating costs. Considering box usage as the sole objective in OR scheduling is not necessarily realistic, however, the authors laid the groundwork for incorporating the SPD into a more comprehensive

multi-objective formulation. This research study included a more comprehensive objective that considered current surgical group preferences along with SPD cost.

Scheinberg et al. [163] conducted a work design study within a SPD. The local hospital had a high number of re-processing incidents due to bioburden, in which an individual instrument was not properly sterilized the first time and the entire instrument set had to be re-sterilized. The authors created a “cleanability” index and re-organized the instrument sets into father-daughter configurations that separated the more difficult to clean instruments from the routine ones. The reconfiguration reduced the mother set reprocessing workload by 85% and the authors calculated annual savings of over \$200,000 in a high-volume setting.

This research study incorporated the SPD. To the author’s knowledge, only Beroule et al. [28] has considered the SPD in a technical OR scheduling paper thus far. In fact, the literature review in [163] stated that the authors could not find any research papers in this area. There are several articles that examine how surgeon preference cards financially impact the OR and/or SPD. These articles are discussed at the end of the literature review.

Uncertainty

Uncertainty makes the largest contribution to the overall difficulty of OR planning. This is the main difference between OR scheduling models and machine job-flow models, in which jobs can generally be assumed ready for processing and the duration of the process is not as variable. OR patients are not always available to begin surgery ahead of schedule if previous surgeries end early. Pre-surgery, surgery, and patient recovery times are highly variable [159]. Several managerial articles examined how to predict surgery durations based on factors such as type of procedure, patient demographic, and surgeon experience. However, even if OR managers have a good estimate of the probability distribution of the durations, OR planning is still difficult.

The most recent literature review found that the percentage of articles incorporating some aspect of uncertainty is generally between 50-60% and peaked at 65% in 2014 [159]. Stochastic duration is more common than stochastic arrival (44% to 28%), and the authors recommended future research lie in patient rescheduling, both on the day of and a couple days prior to surgery. Table 7 shows that articles followed a similar trend from 2015 on, with a slight decrease in overall uncertainty. Fifty-one percent of the articles incorporated some element of uncertainty. Stochastic duration is still more common than stochastic arrival, albeit with a lower proportion (38% and 12%, respectively). Not surprisingly, the vast majority of articles considering stochastic recovery incorporated a downstream unit such as the PACU or a recovery ward.

Patient rescheduling, which often results from uncertainty, has begun to receive attention from researchers. Li, Gupta, and Potthoff [104] developed an algorithm to manually reschedule surgeries two days out that minimized OR staffing costs. The authors found that booking procedures within blocks led to low OR utilization and high staff costs. By having two different shift lengths, the authors achieved significant improvements with data from three separate hospitals.

Table 7: Uncertainty

Deterministic	
<i>Duration</i>	[9, 10, 15, 21, 24, 28, 32, 33, 38, 50, 56, 69, 71-74, 76-78, 82, 83, 91, 96, 102, 104, 107, 112, 114, 119, 122, 123, 125, 126, 128, 130, 143, 146, 147, 151, 154, 155, 157, 160, 166-168, 185, 186, 188, 189, 191-193, 197-200, 211, 213, 214]
<i>Recovery</i>	[1, 15, 21, 27, 72, 101, 102, 142, 168, 186, 209, 213]
Stochastic	
<i>Duration</i>	[2, 5, 16, 19-21, 39, 62, 63, 68, 70, 83, 88, 94, 101, 102, 106, 110, 111, 117, 123, 127, 131, 134, 136, 138, 143, 145, 147, 157, 158, 162, 171, 180, 184, 186, 201, 202, 204, 207, 210, 212]
<i>Arrival (non-elective)</i>	[33, 39, 62, 63, 68, 77, 88, 94, 102, 143, 158, 175, 188, 210]
<i>Recovery</i>	[1, 16, 19-21, 39, 64, 65, 68, 79, 88, 105, 120, 131, 138, 156, 157, 186, 202, 204, 207, 214]
<i>Demand (elective)</i>	[1, 5, 70, 79, 81, 90, 94, 120, 127, 147, 158, 166, 175, 180, 184, 202]
Unclear	[26, 64, 65]

Heydari and Soudi [77] developed a two-stage stochastic program that determined the best rescheduling strategy in the event of non-elective arrivals disrupting the current elective surgery schedule. The authors considered two innovative performance metrics in addition to two traditional performance metrics of overtime and makespan. The new metrics were robustness, or how much the objective value changes because of a non-elective disruption, and stability, which represented the amount of deviation from the original schedule.

As the amount of uncertainty in a model grows, researchers will often use discrete event simulation (DES). DES offers industrial engineers many advantages in healthcare research. DES is relatively inexpensive and easy to implement; researchers can explore various strategies and scenarios and their effect on overall system performance [12, 18, 40, 45, 85, 86, 93, 109, 144, 165, 183]. DES is noninvasive, which allows researchers to explore alternative strategies without adversely affecting a patient's health [135]. For example, DES is often used to consider various strategies surrounding a hospital's Emergency Department prior to implementing any changes, which prevents unnecessary risk to patients [92, 121, 205, 206].

The variability of a process plays a critical role in stochastic environments, and researchers have begun to examine this dynamic. Choi and Wilhelm [43] proved that the smallest-variance first rule is the optimal way to schedule surgeries under certain restrictive assumptions. Recently, researchers have utilized DES to explore the impact of variability-oriented sequencing rules for OR scheduling in a more realistic environment [134, 164, 170]. This research study factored in case variability when developing the SPD workload matrix.

Techniques

Researchers utilize a wide variety of techniques to address the OR scheduling problem. The most recent literature review found that mathematical programming has gradually increased during 2004-2014 to the mid-60th percentile [159]. DES remained relative stable at approximately 30% of

all articles [159]. Heuristics and constructive algorithms followed shortly after that at around 22-25% of articles [159]. The authors identified simulation-optimization as the primary area for future research due to its ability to handle OR scheduling complexities [159].

As table 8 and figure 4 illustrate, certain trends continued while others have not. Mathematical programming continues to be popular and the percentage of articles using mathematical programming increased to nearly 80%. DES remained at approximately 33% of the articles. Constructive algorithms and heuristics saw a significant increase. The increase reflects two trends. First, researchers are adding complexity to their models, which increases computational time for traditional mathematical programming. Second, heuristics and constructive algorithms can dramatically reduce computation time while achieving a relatively small optimality gap. These changes are positive because researchers are adding complexity and reducing computation time.

Researchers often mention how much their algorithm or heuristic reduces computation time compared to traditional mathematical programming optimization using a solver such as CPLEX. Bouguerra, Sauvey, and Sauer [32] decreased from 30-40 minutes to less than 10 seconds. Silva et al. [167] reduced from 4-5 hours to 1-2 seconds while the optimality gap was often very close to 0. Guo et al. [71] decreased computation time for large scale instances of their data from 9-10 hours to 20-30 minutes while the average optimality gap remained less than 10%.

Though still relatively scarce, researchers have started to use simulation-optimization. Zhang and Xie [212] used it to determine optimal surgeon arrival times for a multi-OR suite in China. Liang, Guo, and Fung [106] utilized surface response method to find the optimal combination of three scheduling rules using a simulation-based model. Goal programming has seen a decline recently, with only two articles since 2015. Li et al. [105] used lexicographic goal programming to find the optimal block schedule for surgeons. The authors considered four goals: patient waiting time, OR utilization, recovery bed utilization, and recovery bed levelling. Visintin et al. [186] initially started out with a MIP model in developing an OR scheduling system in Italy, however, the authors eventually used

goal programming because the stakeholders appreciated the flexibility of the technique. It also helped avoid infeasibility issues. Goal programming can be useful in OR scheduling because it can model multiple objectives and is a balance of efficiency and robustness for daily computations [174].

Table 8: Methodology

Simulation	
<i>Monte Carlo</i>	[15, 20, 83, 101, 102, 110, 136, 214]
<i>Discrete Event</i>	[1, 16, 19-21, 33, 62, 63, 81, 90, 91, 94, 96, 106, 120, 123, 127, 131, 134, 138, 143, 147, 156-158, 162, 180, 184, 186, 199, 204, 207, 210, 212]
Mathematical Programming	
<i>Linear Programming</i>	[5, 15, 28, 32, 38, 54, 56, 69, 72, 73, 77-79, 91, 94, 102, 105, 111, 117, 119, 123, 125, 131, 151, 157, 175, 184, 191, 202]
<i>Integer Programming</i>	[1, 27, 38, 50, 56, 71, 76, 94, 101, 104, 122, 127, 136, 154, 156, 167, 202, 213]
<i>Mixed Integer Programming</i>	[9, 10, 21, 26, 28, 38, 54, 62, 64, 65, 68-70, 72-74, 77-79, 82, 88, 91, 102, 107, 110-112, 114, 116, 117, 123, 126, 128, 130, 131, 138, 142, 143, 145-147, 151, 155, 157, 160, 162, 168, 171, 180, 185, 186, 188, 189, 191-193, 197-201, 209, 212, 214]
<i>Constraint Programming</i>	[67, 76, 102, 192]
<i>Other (such as goal programming)</i>	[16, 24, 38, 105, 145, 186]
Heuristic	
<i>Simulated Annealing</i>	[19, 39, 73, 74, 125, 171]
<i>Genetic Algorithm</i>	[69, 71, 73, 102, 116, 160, 189, 214]
<i>Particle Swarm Optimization</i>	[28, 193]
<i>Other</i>	[21, 32, 54, 62, 68, 70, 74, 90, 94, 101, 106, 107, 119, 125, 130, 145, 154, 155, 160, 162, 167, 171, 184, 189, 191, 193, 197-200, 211]
Constructive algorithm	[2, 15, 20, 33, 38, 39, 50, 56, 67, 68, 70, 76, 81, 83, 87, 90, 101, 102, 104, 106, 107, 119, 122, 123, 125, 126, 128, 131, 134, 136, 146, 151, 154-156, 162, 171, 188, 189, 191, 201, 202, 212, 213]
Sample Average Approximation	[79, 88, 111]
Branch and Price Algorithm	[76, 130, 136]
Column Generation	[76, 107, 130, 136]
Markov Chain Modeling	[166, 207]

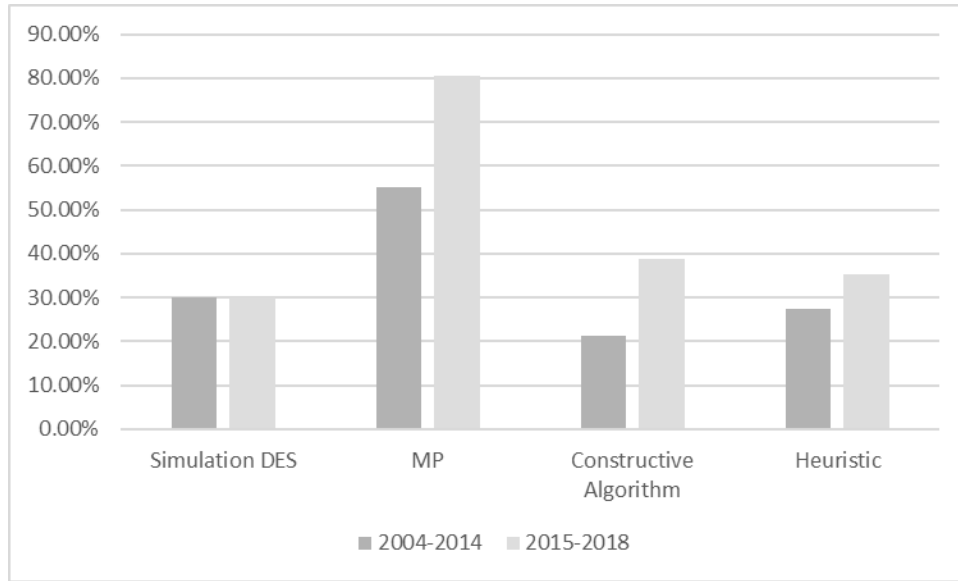


Figure 4: Proportion of Methodology

Thus, future areas of research lie in exploring how simulation-optimization and goal programming methods can accurately and efficiently aid in solving OR scheduling problems. Furthermore, the use of simulation models to test the results of mathematical programming and algorithmic/heuristic solutions is also recommended. Simulation can be used to test the results of mathematical models to predict their performance [3, 22, 35]. Heuristics or simple scheduling policies that are easy for hospital management to implement can then be derived from the simulation results [84].

This research study used goal programming in the preference card optimization model and in one of the block assignment scheduling models. The research also utilized a combination of mathematical programming and simulation to validate the mathematical models' results.

Testing and Application

Testing and application refers to whether researchers used data, either theoretical or real, to examine their model's effects and if the model was implemented in practice. As Samudra et al. [159] noted, testing serves two purposes. First, it can provide insights into the computational efficiency of

the model. Second, it can show whether the model improves the desired performance measures or not. Healthcare research is a practical, not theoretical field, and the testing and application aspect is critical.

The most recent literature review found that researchers have begun to use real data, often from local hospitals, much more frequently than in the past [159]. This reflects the improvement and accessibility of electronic medical databases and researchers' acknowledgement of the need to test their models using real data. Despite the increased use of real data, the percentage of articles that actually implemented their model is low, remaining below 7% [159]. Furthermore, in the articles that did involve implementation, the authors rarely discussed the associated real-world challenges. Discussing implementation challenges can greatly aid other researchers in learning what factors contributed to successful implementation. Samudra et al. [159] recommended better implementation rates, discussing implementation challenges, and having more reproducible research, such as making their data accessible to others so that they can see if the model generalizes to their hospital settings or not [159].

This literature review found virtually identical trends for testing and application, as shown by table 9 and figure 5. However, authors are beginning to discuss implementation challenges in more detail. Zenteno et al. [209, 210] provided two excellent examples for discussing model implementation. The authors used a data driven scheduling strategy to pool open blocks to reduce non-elective surgery wait times [210] and then extended the model to smooth recovery bed utilization [209] in a Massachusetts hospital. The authors achieved considerable success with model implementation. Wait time decreased by 25.5% despite a 9% increase in patient volume, while the peak weekly recovery bed usage decreased by 3.2% despite a 2.8% average census increase. The authors discussed in detail the implementation phase and emphasized two factors critical to their success. The first was engaging and receiving buy-in from hospital leadership and the second was in-depth discussions with surgical services. Once hospital leadership buy-in was achieved, there was a

trickledown effect of culture change for the better. Surgical services provided invaluable feedback as to what constraints were most important when considering potential schedule changes.

Table 9: Applicability (Note: some articles use both real and theoretical data)

Real Data	[1, 5, 9, 10, 15, 16, 19, 21, 24, 26, 27, 38, 50, 54, 56, 62-65, 68-73, 77, 81-83, 87, 88, 90, 91, 94, 96, 101, 104-107, 111, 114, 116, 117, 119, 120, 123, 125, 127, 130, 131, 134, 136, 138, 142, 143, 145-147, 151, 154-158, 160, 162, 166-168, 171, 175, 180, 185, 186, 189, 191-193, 197, 198, 200-202, 204, 207, 209, 210]
Theoretical Data	[2, 20, 28, 32, 33, 39, 67, 72, 74, 76, 78, 79, 102, 126, 128, 131, 154, 188, 191, 197, 199, 211, 212, 214]
Model Implemented in Real Life	[27, 54, 87, 138, 145, 186, 209, 210]

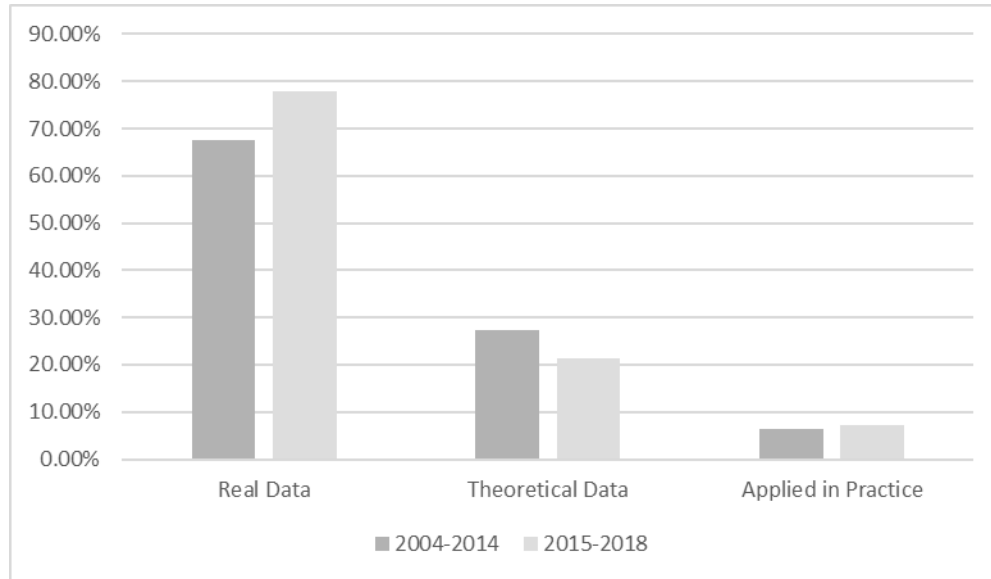


Figure 5: Applicability Usage

Systematic testing and validation was critical for Rath et al. [145] to convince management that the DSS derived from their model would reduce costs at the UCLA medical center. After the DSS was implemented, the authors estimated annual savings of 2.2 million dollars [145]. Researchers can refer to Benchoff et al. [27] and Visintin et al. [186] as other excellent examples of model implementation.

Thus, future research lies in continuing upon these examples of model implementation. Additionally, as data sets become more accessible, authors can test their models using data sets from different hospital settings to determine if their model is generalizable or not. Leefink and Hans [103] recently generated a large benchmark set for surgery scheduling for researchers to use for their models.

This research study included real data, both historical and observed. The study also generated theoretical data based on previous research and discussions with hospital staff. While the research study did not include model implementation, the research models were thoroughly tested using simulation.

Geographic Location

OR scheduling research occurs throughout the world. The purpose of this new section is to provide insight about where OR scheduling research is occurring. Literature reviews can help researchers collaborate with one another on future works. Researchers can also share data to see if their models generalize to other locations and settings. An article is considered to take place at a certain geographic location if the authors use real data from that location. Articles that only use theoretical data are not considered. If the authors ambiguously stated the hospital location, such as “an Italian hospital,” then the location of the primary author or the author who was listed as being from a hospital was used. Table 10 displays articles by geographic location and figure 6 is a map that displays the information visually. The size of the markers in figure 6 correspond to the frequency, with larger markers indicating a higher frequency.

The United States and China are the most common countries for OR scheduling research. Within the United States, the most popular location is the Mayo Clinic (4 of the 20 articles). Most of the remaining locations within the United States lie in the Northeastern and Midwestern parts of the country. Europe is the continent with the most articles, with Italy being the most common country.

There are many areas of the world that need more research, such as Central and South America, Africa, Eastern Europe, Asia (excluding China), rural areas in the United States, and Australia. A promising area for future research lies in examining model generalization. For example, do models in China extend well to data in Europe or North America? Do models developed in urban areas in the United States extend to rural areas? The answers could encourage collaboration and development of more generalizable models in the future. Furthermore, authors are encouraged to provide a more specific description of the location. Many articles only state the country of origin.

Table 10: Geographic Location

North America	
United States	[1, 21, 27, 62, 70, 81, 90, 96, 107, 120, 130, 134, 136, 138, 145, 147, 166, 197, 209, 210]
Canada	[87, 155, 162, 207]
South America	
Chile	[19, 56]
Brazil	[167, 168]
Europe	
Belgium	[50, 158, 180, 192]
France	[32, 33]
Germany	[64, 65, 94, 143]
Netherlands	[88, 105]
Norway	[151]
Italy	[15, 24, 34, 69, 101, 112, 116, 185, 186]
Portugal	[38, 117, 119]
Spain	[54, 123, 125]
Sweden	[91]
Wales	[156]
England	[142]
Asia	
China	[71, 82, 83, 110, 111, 114, 175, 189, 191, 193, 198, 200, 201, 212]
Japan	[122]
Indonesia	[160]
Africa	
Egypt	[202, 204]
Tunisia	[72, 157]
Middle East	
Iran	[68, 73, 77, 79, 146]
Jordan	[9, 10]
Australia	[171]

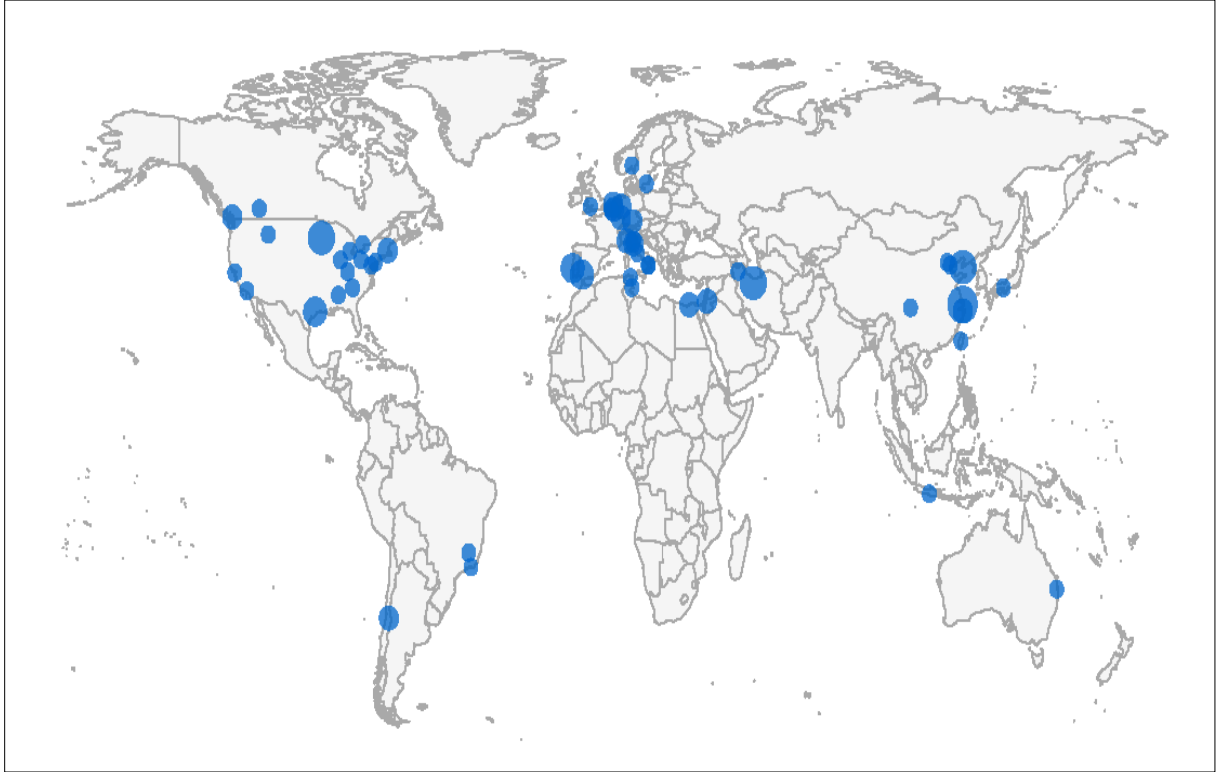


Figure 6: Geographic Map of Article Locations and Frequency

Summary

This literature review covered technical OR scheduling articles. It used a similar classification scheme as recent literature reviews and included a new category, geographic location. Table 11 summarizes trends, areas for future research, and changes from the most recent literature review. While many of the same trends have remained the same, others have changed and select areas of future research have begun to receive attention.

Table 11 also summarizes this research study's fit or contribution to each classification. **The most novel aspect of this research study from an OR scheduling perspective is the inclusion of the SPD into a technical OR scheduling model.** In addition to OR scheduling, there is an emerging body of research on the SPD and preference cards that is related to this research.

Table 11: Literature Review Summary

	Trends		Recommended Future Research		This Research Study
	2004-2014 [159]	2015-Present	2004-2014 [159]	2015-Present	
Patient Type	Virtually all consider elective, 27% consider non-elective	Virtually all consider elective, 23% consider non-elective	Outpatient cases, Patient bulking	Outpatient cases, Non-elective cases, Centralized vs. decentralized OR for non-elective	Elective and Non-elective
Performance Measures	Waiting time, overtime, utilization most common	Most PM's are increasing in usage due to increasing trend in multi-objective modeling	Behavioral PM's	Behavioral PM's	Preferences, SPD workload
Decision Delineation	Patient-centered most common	Patient-centered most common, increasing trend in multiple decisions in models, shorter time horizons most common	Dynamic Scheduling	Dynamic scheduling, avoid ambiguous scheduling terms, clearly state planning horizon	Surgeon/group – date/room, one week horizon, block scheduling
Upstream/ Downstream Units	Approximately half consider at least one external unit, majority focusing on downstream	Approximately half consider at least one external unit, improvement in ICU and other upstream units	Non-traditional units, upstream units	Increase in articles considering at least one external unit, non-traditional units, upstream units	SPD
Uncertainty	50-60% consider uncertainty, with peak of 65% in 2014, stochastic duration most common	Slight decrease in uncertainty (51%), stochastic procedure duration most common	Patient rescheduling	Patient rescheduling, less completely deterministic models	Incorporates uncertainty through simulation model
Techniques	MP increasing, simulation constantly around 30%	MP continues to increase, simulation remains constant, algorithms/heuristics more common	Simulation-optimization	Simulation-optimization, goal programming, use of simulation to test MP results	MIP, goal programming, DES
Testing and Application	Increased use of real data, poor implementation rates	Increased use of real data, poor implementation rates	Implementation, reproducible research, discussing implementation challenges	Implementation, discussing implementation challenges, reproducible research,	Primarily real data, model testing via DES
Geographic Location			United States, Europe and China most common	Model generalization, more research in certain areas (e.g. rural United States)	Rural United States

Preference Card/SPD Related Research

As supply chain costs can represent up to 40% of a hospital's budget with 61% of that coming from perioperative services [46], there is an emerging research trend in the last 10 years involving OR supplies, instruments, and surgeon preference cards. The research area falls into three major types: observational, reduction, and technical. Within those categories, the research may involve reusable and/or disposable instruments and supplies. Observational research involves studies where preference cards are analyzed or where the actual usage rates of OR supplies and instruments for certain types of surgeries are recorded. Researchers will then often calculate the associated cost of waste and extrapolate that into a potential estimated annual savings amount. This includes disposable supplies that are opened but not used or reusable instruments that are picked for the case but unused and must go through the sterilization process again. Calculating disposable supply costs is usually straightforward and involves the purchasing department looking up per unit costs. Calculating reusable instrument costs is much more difficult and may involve SPD labor costs, instrument depreciation/wear-out and purchase costs, and the SPD's annual budget.

Reduction research often includes observational studies, but the focus of these papers is on the actual reduction of preference cards and the post-implementation results. The methodology for reducing preference cards is usually group consensus with the surgeons involved based upon collected usage rate data. Much like the observational research, post-implementation results often focus on the associated cost reduction. However, authors also discuss other important consequences of preference card reduction, such as the impact on surgical times, the number of times a surgeon requests an instrument/supply during a case but it is not present in the OR and must be retrieved, and OR staff opinions on the new cards.

Technical research is much less common than observational or reduction research. Technical research involves mathematical or simulation modeling. The mathematical model may attempt to

optimize the number of instruments in a tray and the number of trays in a preference card for a given case. It also may optimize other processes involving the SPD such as inventory management or SPD machine scheduling. The simulation models examine how operational decisions such as SPD staffing or equipment levels affect performance metrics of interest.

Two observational studies highlighted the disposable supply cost variation amongst different surgeons performing the same type of surgical procedure. Allen et al. [13] collected and analyzed the laparoscopic cholecystectomy preference card of 10 different surgeons in 2002 at the University of Louisville teaching hospital. They calculated disposable instrument costs for each card and found that costs ranged from \$92 to \$637, which was a significant amount of variation. In 2011, Chu et al. [44] analyzed surgeon notes, invoices, and preference cards for laparoscopic appendectomies and found that the disposable costs per case ranged from \$299 to \$552 and theoretical costs ranged from \$81 to \$873. The authors estimated potential annual savings of \$22,437 if the preference cards were optimized and standardized across surgeons.

Two observational studies illustrated the relatively low usage rates of reusable OR supplies. In 2014, Stockert and Langerman [172] observed 49 total otolaryngology, plastic, bariatric, and neurosurgical procedures and found that the average instrument usage rates were 13.0%, 15.5%, 18.2%, and 21.9%, respectively. Furthermore, as the number of instruments per tray increased, the average usage rate decreased and the instrument error rate (either a missing or a broken instrument) increased. The authors also calculated that the instrument reprocessing cost was \$0.51 or more per instrument. In 2016, Van Meter and Adam [181] observed 28 gynecologic cases and found that the average usage rate was 20.5%. Like Stockert and Langerman [172], Van Meter and Adam [181] found that instrument usage inversely correlated with the number of instruments per tray. The authors also estimated there were \$230,160 in excess annual costs through this inefficiency, however, their calculated cost of \$3.19 per instrument processed was probably an overestimate because it included several fixed costs.

Three observational studies calculated mean disposable waste cost per case for neurosurgical or colorectal procedures in 2017. Rigante et al. [150] observed 53 endovascular procedures in the Netherlands and recorded disposable supplies that were opened but unused. The authors calculated an average wasted cost of €515.09 per case [150]. Zygourakis et al. [215] performed a similar study for 58 neurosurgical procedures and calculated an average waste cost of \$653 per case, which extrapolated to \$2.9 million based on their volume . Finally, Billings et al. [29] observed 50 colorectal cases and found there was an average waste cost of \$368. Interestingly, the authors told the surgical team that the observer was recording instrument usage in 35 cases and withheld this information in the other 15 cases but found no significant difference in average waste cost between the two scenarios [29].

In the last six years, there has been a trend in reduction research papers. In 2012, Penn et al. [141] were able to eliminate 12 of 40 disposable items in tonsillectomy and adenotonsillectomy cases which would result in \$17,149.50 in savings over the next year. The authors also calculated that the reduction in waste resulted in 3000 lbs. less of trash per year which would save an additional \$830.59. Chin et al. [42] reduced the number of instruments per tray for five common head and neck cases. After observing 226 trays, the authors created new trays based on instruments that had usage rates of 20% or more, which reduced the average tray size by 57%.

Three reduction research papers focused on pediatric laparoscopic appendectomy cases, which are among the most common surgical cases for children in the United States [17]. Through group discussions and surgeon consensus, Avansino et al. [17] went from 10 individual surgeon preference cards to one standardized card, which resulted in a \$167 (20%) reduction in average cost per case with estimated annual savings of over \$41,000 based upon their volume . The authors also conducted a post-implementation survey amongst OR staff and found generally positive results about the new standardized card [17]. Similarly, six surgeons created a standardized preference card at Primary Children's Hospital in Salt Lake City that decreased the average cost per case from \$844.11

to \$305.32, with savings of \$195,041.98 for the first year alone [169]. The authors also found no significant difference in post-operative outcomes with the new standardized card, while median operative times slightly increased from 34.8 to 37 minutes [169]. Finally, Robinson et al. [152] performed a study in which they did not create a standardized preference card, but instead implemented software that provided surgeons real-time feedback of current supply cost data during a case. They also provided monthly individualized reports to the surgeons detailing their supply costs and found that the median cost per case decreased from \$884 to \$388 [152].

Reduction research papers have covered a variety of different case types. Albert and Rothkopf [11] removed 15 disposable items from their plastic packs and 7 items from their hand packs, which they calculated would save \$17,381.05 annually. The authors also started a recycling program at their three Massachusetts hospital campus and estimated this would result in annual savings of \$41,844 [11]. Farrokhi et al. [59] applied a 5S to their spine case preference card and reduced the number of instruments from 197 to 58 without increasing surgery times. They estimated that this could result in up to \$2.8 million in annual savings. Similar to [172, 181], the authors found that larger instrument volume correlated with high instrument availability and defect errors [59]. Harvey et al. [75] used a one-time surgeon survey to remove 109 disposable supplies from 39 gynecological preference cards, with an estimated \$18,213.07 in savings over three months.

Farrelly et al. [58] eliminated 1,826 instruments from their pediatric surgery preference cards and estimated between \$53,193 to \$531,929 in annual savings, while still receiving positive feedback from OR staff. Finally, Koyle et al. [97] created a single standardized preference card from two different preference cards for pediatric inguinal hernia repair after observing usage rates for the two different cards. Trimming the two cards down from 96 instruments/13.5 lbs. and 51 instruments/11.2 lbs. respectively, to 28 instruments/ and 7.8 lbs. reduced the sterilization cycle time from 11 and 8 minutes to under 5 minutes, saved \$11.73 and \$34.68 per tray in processing costs, and received positive post-implementation staff feedback via surveys [97]. The above observational and reduction

research illustrates how preference cards are often inefficient and that improving them can result in significant financial savings.

There are a few technical research papers involving SPD inventory management or other SPD processes. In a recent literature review on materials logistics in hospitals, Volland et al. [187] identified only 3 papers (out of 145) that involve sterile medical devices (the papers are [140, 176, 179]). Fineman and Kapadia [60] established stock levels for OR instrumentation assuming constant demand. The authors split the stock into two different categories: processing stock to meet daily demand and replenishment stock to account for replacing damaged instruments and the potential of supplier failure [60]. Nilson [133] discussed methodologies to determine optimal OR equipment and instrument levels. The author provided more of an overview and case study type description than detailed quantitative models. Diamant et al. [53] modeled OR instrument sterilization as a discrete-time Markov Chain and derived optimal base-stock levels. Ozturk et al. [140] used a branch and bound heuristic to determine the optimal SPD washing machine schedule that minimized the sterilization process makespan. Tlahig et al. [176] used MIP to compare the total costs of a decentralized and centralized sterilization network.

Approximately 10 years ago, multiple researchers, many of whom were from the University of Twente in the Netherlands, examined the SPD's role in the surgical process and sought opportunities to gain efficiencies. In a Master's thesis, Kroes [99] conducted an in-depth study of a SPD and found three primary sources of inefficiency: 1) high rate of unused instruments, 2) high rate of emergency sterilizations, and 3) large and heavy instrument trays. Wolbers [195] modified the tray compositions surrounding 11 different surgery cases and estimated annual savings of between €55,000 - €65,000.

Florijn [61] developed an optimization model that decided how instruments are assigned to trays and trays are assigned to preference card, which the author referred to as the Tray Optimization Problem (TOP). The objective was to minimize the number of trays, instruments, and tray handlings.

Constraints included maximum weight/volume of trays and required instruments for a given case [61]. The author used simulated annealing to solve the model and estimated annual savings of €125,000. Considering this model only dealt with 12 of the 550 trays in the OR department, the author noted that potential savings for optimizing the entire department's trays could be several million euros [61]. Reymondon et al. [148] also addressed the TOP but the objectives were to minimize storage and reprocessing costs. Van de Klundert et al. [179] developed an integer linear program for a modified TOP, however, the objectives were related to instrument/tray storage and usage costs. The authors also examined optimal inventory levels and simulated how different inventory policies would perform under stochastic settings [179].

The most recent published work on the TOP is by Dobson et al. [55], who slightly modified the formulation from Reymondon et al. [148] and developed a heuristic that solved similar sized problems more efficiently. Dobson et al. [55] also analyzed how the OR surgical schedule impacts the optimal tray configuration. Finally, in a developing work, a Ph. D. student from Ohio University is building upon the TOP by including an objective term that maximizes instrument utilization rate and creating a new heuristic to solve the problem [6]. **This research study differed from previous TOP models in that it 1) used goal programming in lieu of traditional mathematical programming and 2) considered expected instrument non-usage rates.**

In addition to optimization, simulation is another effective tool to study the SPD. Casati [37] used an Erlang-C queueing system to determine the optimal number of SPD staff required per tray type for every 30 minute time block. Di Mascolo et al. [52] developed a DES model to examine how smoothing the container arrival rate into a French hospital SPD improved overall performance of the system. Lin et al. [108] built a simulation model to help aid operational decisions, such as staffing and equipment levels, during a SPD expansion and redesign project. Performance measures included tray turnaround time, WIP, and the number of delayed cases. Most recently, Di Mascolo and Gouin [51] developed a generic DES model that can be used by fellow researchers and practitioners to model

their own SPD, using either local or global data. The simulation model in this research study builds upon Di Mascolo et al. [52] by linking the container arrival rate to the actual OR system and not controlling it as a fixed input parameter.

Contributions of Research

Researchers have extensively studied OR scheduling through a variety of angles in the last decade. A recent literature review on the topic considered 216 OR scheduling research papers from 2000-2014 [159]. As a research contribution, this study conducted a literature review of technical OR scheduling articles from 2015 to early 2018, totaling 113 articles. This study had two research contributions that addressed gaps identified in this literature review. They were incorporating the SPD into technical OR scheduling models and developing a new TOP model. Additionally, this study developed a simulation model of an OR suite and its SPD to test the results of the models that addressed the research gaps.

CHAPTER THREE

METHODOLOGY

The research occurred at Montana State University, using data based on processes at Bozeman Health Deaconess Hospital (BHDH). BHDH is a Level III trauma center serving the city of Bozeman and the surrounding population of Southwestern Montana. It has an eight-room OR suite that sees approximately 6,000 patients annually, not including OBGYN deliveries which utilizes a dedicated OR. Hospital management was initially interested in improving SPD throughput and its impact on the OR suite. Management also thought that instrument usage rates for certain surgical procedures were low and that the weight of the instrument trays was high.

Participants

The research involved several hospital staff at BHDH. The SPD manager served as the primary point of contact for the research conducted inside the SPD. The SPD manager, along with a handful of SPD staff that had several years' experience, served as the subject matter experts on current SPD procedures. The Surgical Services Manager and OR Core Coordinator served as the primary points of contact for the research conducted inside the OR. The OR Core Coordinator is heavily involved in the OR instrumentation inventory and works closely with the surgeons on their preference cards. The Core Coordinator has over 15 years of experience at BHDH.

The BHDH System Manager of Project Management served as the primary point of contact for the overall research project. The System Manager served as the liaison for any relevant staff outside of the SPD or the OR that the author needed to communicate. The research did not use BHDH patients as participants. Besides the previously mentioned staff and their departments, the research primarily used historical data from the OR.

Materials

The research primarily utilized two separate software programs. For the simulation model, the software Arena version 15.1 was used. The author previously used this software to develop an OR simulation model in [134]. For the mathematical models, the optimization software AMPL version 3.1 was used.

Models

The objectives of the research were to build a mathematical decision model that optimally allocates the block schedule and to build a mathematical model that assigns surgical instruments and trays to procedures. A comprehensive SPD simulation model that is a part of a larger OR simulation model was developed to test the mathematical models' results. This section outlines the inputs, outputs, structure, and software for the models. The final section of this chapter outlines the data collection that was conducted for the models.

OR Block Assignment Model

The primary inputs into the block assignment model were the current OR block schedule, surgical group block preferences, and the SPD workload matrix. The SPD workload matrix represents the effect on total SPD processing time if two different surgical groups are operating during the same block. This study examined four different calculation methods for developing the matrix. This provided insights for future research as to what types of formulae are effective when developing the workload matrix. Then, two additional block assignment models were formulated and tested to compare to the first block assignment model. This provided insights for future research as to what type of model is effective for this problem. Furthermore, these experiments tested the methodology's robustness. Chapter four discusses this in greater detail.

The block assignment model included all applicable constraints such as the number of blocks each group required. Sensitivity analysis examined how weighting the two different objective terms affected the optimal schedule. The outputs of the models were block schedules that considered the SPD workload.

Preference Card Model

Inputs to the preference card model included instrument usage rates, instrument preferences for procedures, and instrument weights. As in previous Tray Optimization Problem (TOP) articles, approximately 12 total surgical procedures were considered. A mathematical model that optimized preference cards using goal programming was formulated. Goal programming can be a more effective technique than linear programming when there are several objectives in the model. It has been used sparingly by previous researchers in OR scheduling [3, 4, 30, 47, 105, 139, 174], but not in the TOP. The first goal of the model was to minimize the annual expected number of unused instruments. The second goal was to minimize the annual number of instruments that were requested but not assigned to a surgical case. The third goal was to minimize the amount each tray exceeded its industry regulation of 30 pounds. The formulation was solved using the software AMPL version 3.1. The output of this step was the assignment of instruments and trays to preference cards.

Simulation Model

Inputs to the simulation model included the existing OR simulation model previously developed in [134], the probability distributions for OR surgery times, SPD manual rinsing times, SPD assembly times, and the block schedule output from the block assignment model. The conceptual OR simulation model developed by [134] is shown in figure 7. The primary performance metrics of interest in [134] were number and magnitude of tardy surgeries. A typical one week OR schedule with the current block allocation was compared to the block schedules resulting from the block assignment models.

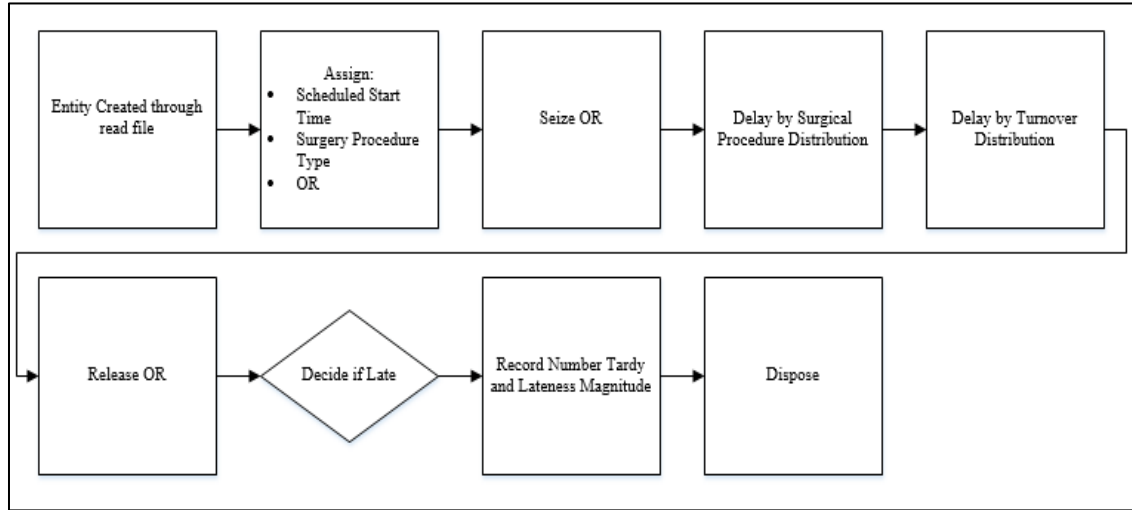


Figure 7: OR Conceptual Model

Probability distributions for the stochastic steps in the SPD process were calculated using the software Input Analyzer. The simulation model was then verified and validated. The simulation model was used to test the mathematical models' results and their anticipated impact on SPD performance. Add-on cases were created each day according to historical rates and were accommodated into the existing surgery schedule.

Data Collection

The research study required several pieces of data. First, a three-year historical data set of all OR procedures from BHDH was used. The data set contained information such as start time, end time, and surgeon for 18,071 unique surgeries and 567 different surgical procedures. The author previously used the data set to determine probability distributions for the different surgical procedures, which were then used for the OR simulation model in [134]. These surgical procedure probability distributions were used in the OR portion of the comprehensive simulation model. A similar historical data set covering January 2018 through June 2018 was also used. The data set was used to generate the baseline OR schedule for the comprehensive simulation model and to determine probability distributions for additional types of surgical procedures.

The manual rinsing times in the SPD decontamination area and the manual assembly times in the clean side of the SPD were collected by direct observation. The collected data was used to calculate the probability distributions for the manual rinsing times by surgical case type. For the manual assembly times, the category (tray, wrap, peel pack, and type of tray) and total time to assemble the item were collected. Similar to the manual rinsing times, the assembly time probability distributions were calculated by item type. As a part of collecting these processing times, the SPD structure was observed, to include the flow of instruments, staffing schedule, and number of automated machines such as the decontamination area washing machines and the autoclaves. This data was used for the SPD portion of the simulation model.

This research study also utilized the electronic BHDH SPD productivity report. The electronic report detailed the number of peel packs, wraps, and tray processed each day by the SPD. The electronic report was combined with the historical OR schedule from that same time period to estimate the proportion of OR and non-OR items processed by the SPD.

The most common tray recipe lists were collected. The tray lists do not contain the weight of each type of instrument, however, this information was generally found with a Google search. In cases where a specific instrument's weight was not found, then it was assigned similar instrument's weight (e.g. forceps, scissors, etc.). This information was used for the preference card model.

The block time preferences of the different surgical groups were quantified using a Likert scale [132]. Assigning a 1 represented a surgical group retaining its current block. If the surgical group had block time for the same day but in a different OR, then it received a score of 2 (similar type OR) or 3 (different type of OR). A surgical group assigned the same OR but on a different day received a 3 or 4. A surgical group assigned a different OR on a different day received a 4 (similar type OR) or 5 (different type OR).

Initial tray usage rates were collected by speaking to the OR tech immediately following the procedure and systematically going through and marking whether each tray on the preference card

was used or not. Notional instrument usage data was generated based upon previous TOP models and discussions with the OR Core Coordinator and SPD technicians. The instrument usage rates were used for the preference card model.

CHAPTER FOUR

BLOCK ASSIGNMENT MODELS

This research study developed three block assignment models that maximize surgical group schedule preferences and minimize the SPD cost. SPD cost refers to the time needed to manually process trays from the surgeries. The first model, known as the Block Assignment Model Quadratic (BAMQ), includes quadratic terms in the objective function and all linear constraints. Within the BAMQ, four different calculation methods for the surgical block cost interaction term were developed. A systematic model evaluation plan that altered model run time, calculation methods, and objective weights was implemented to examine BAMQ robustness and calculation method effectiveness.

The second model, known as the Block Assignment Model Linear Goal Programming Deviation (BAMLGPD), is a linear model. Instead of minimizing total SPD cost, the BAMLGPD model minimizes the difference in total SPD cost between different days. A systematic model evaluation plan that altered model run time and objective weights was implemented to examine BAMLGPD robustness. The third model, known as the two-phase Block Assignment Model Linear Goal Programming Deviation (2BAMLGPD), minimizes the SPD cost of the BAMLGPD model in the first phase and maximizes surgical block preferences in the second phase.

This chapter is organized as follows: section one describes the backgrounds and assumptions of the models. Section two covers parameter development. Section three reviews the BAMQ model. Section four details how the SPD workload matrix terms for BAMQ were calculated. Section five covers the BAMQ evaluation plan and results. Section six reviews the BAMLGPD model. Section seven reviews the 2BAMLGPD model. Section eight covers the BAMLGPD and 2BAMLGPD evaluation plan and results. Section nine compares the BAMQ and BAMLGPD models. Section ten addresses model limitations and areas for future research. Section eleven summarizes the results.

Section 1: Background and Assumptions

The three block assignment models address the same problem: what is the optimal block schedule that maximizes surgical group preferences and minimizes the SPD cost? The output of the models is a schedule that assigns block times and ORs for the surgical groups over the planning horizon. The planning horizon for the model is one week. The parameters of the model include the number of ORs and block times, surgical groups with predetermined weekly capacities and preferences for different block times, and a SPD cost term for each surgical group.

The models require certain assumptions to be effective. First, the OR suite must adhere to a block schedule. OR suites in which surgical groups frequently exchange block times would not benefit from the model. The second assumption is that hospital management has effectively allocated capacity to the surgical groups, meaning surgical groups will have a high utilization for their scheduled block time. In other words, if the allocated capacity to different surgical groups is not efficient, then surgical groups with under allocated capacity will likely use block time of surgical groups whose capacity is over allocated. This results in a block schedule that is not followed in practice. The model also assumes SPD staffing is consistent, meaning the time required for the SPD to process cases does not vary across the planning horizon.

Section 2: Parameter Development

This research study used parameters based on data from BHDH. The model had seven ORs with a planning horizon of five days and one time slot per OR per day. The majority of block assignments allocated one group per OR per day. There are 35 possible block time-OR combinations in the model. The two model parameters that required significant development were surgical group preferences for block times and surgical group SPD cost terms. The remainder of this section describes the development of those parameters.

To quantify surgical block preferences, the model utilizes a Likert scale [132]. Block times that are most desirable for a surgical group receive a score of 1 while the least desirable times receive a 5. This inverting of the scale allows the objective function to minimize both the surgical preferences and the SPD cost. This research study approached surgical group preferences from the perspective of minimizing the changes to the existing OR schedule. Unless an OR suite is undergoing expansion, then there is likely an existing block schedule in place. In practice, implementing significant changes to an OR schedule is more difficult than implementing minor changes. Furthermore, showing surgical groups that the model attempts to minimize changes to the status quo may help with stakeholder buy in, which has been shown to be a key factor in successful implementation [209, 210].

Surgical group preferences were generated in the following manner. A 1 represents a surgical group retaining its current block. If the surgical group has block time for the same day but in a different OR, then it received a score of 2 (similar type OR) or 3 (different type of OR). A surgical group assigned the same OR but on a different day received a 3 or 4. A surgical group assigned a different OR on a different day received a 4 (similar type OR) or 5 (different type OR). Thus, the current baseline schedule has an overall preferences cost of 35, which can be compared to schedules generated by the block assignment models.

The SPD cost term for each surgical group, referred to as C_i , represents the expected average total time in minutes for SPD staff to process the daily caseload of surgical group i . C_i refers to the manual rinsing and assembly steps within the sterilization process and not the entire process because the other steps do not vary by surgical case type. To develop C_i , a typical week-long schedule was generated based off of historical data from a BHDH dataset. This schedule served as the basis for the C_i calculations. BHDH does not follow a strict block schedule, with different surgical groups often swapping or filling in different groups' block times. The generated schedule assumed a strict adherence to the existing block schedule. The research study also assumed that if a surgical group

has multiple blocks throughout the week, then it has multiple C_i for each of its block times. This assumption is not necessary for the model but was made based off of historical data, conversations with the OR manager and OR core coordinator, and personal observation revealed the same surgical group's caseload often varied depending on the weekday. Surgical groups with multiple blocks tended to have a higher volume and more complex caseloads on Tuesdays and Wednesdays. Patients did not want to spend the weekend in the recovery ward, meaning less complex cases tended to occur at the end of the week. C_i is calculated as:

$$C_i = n_i(\bar{R}_i + \bar{A}_i) * SCV_i \quad 4.1$$

where n_i equals the number of surgical procedures per block for surgical group i , $\bar{R}_i + \bar{A}_i$ is the sum of the average SPD rinse time and average SPD assembly times of the caseload for group i , and SCV_i represents the scaled caseload coefficient of variation (CV) of surgical group i . The SPD rinse and assembly times are the two manual stations in the SPD that depend on the surgical case type. $\bar{R}_i$ and $\bar{A}_i$ were calculated based off direct observation of the SPD. The SPD data collection methodology will be detailed in chapter 6. SCV_i is given by:

$$SCV_i = 1 + \frac{\frac{\overline{CVR}_i + \overline{CVA}_i}{2}}{\max_{i \in I} \left\{ \frac{\overline{CVR}_i + \overline{CVA}_i}{2} \right\}} * 0.3 \quad 4.2$$

SCV_i is essentially a 0 – 30% addition given to C_i depending on its relative caseload assembly and rinse coefficient of variation (CV) ($\overline{CVR}_i$ and $\overline{CVA}_i$, respectively). The surgical group with the maximum average caseload rinse and assembly CV, $\frac{\overline{CVR}_i + \overline{CVA}_i}{2}$, is given a 30% increase, while all other surgical groups are given an increase between 0 and 30% relative to the maximum. This was done to account for surgical groups with a higher variability, similar to the in-between buffer time calculation from [134].

The generated C_i for the 35 groups had an average value of 244.18 minutes, median of 212.81 minutes, standard deviation of 150.92 minutes, minimum of 33.62 minutes, and maximum of 715.44

minutes. After the BAMQ is described in section three, section four details how the SPD workload matrix term between two surgical groups assigned the same block time, $S_{ii'}$, is calculated using their respective C_i 's.

Section 3: BAMQ

The BAMQ is formulated as follows:

Parameters:

P_{ijk} = preferences for surgical group i ($i = 1, 2, \dots, I$) to have OR j ($j = 1, 2, \dots, J$) during block time k ($k = 1, 2, \dots, K$)

$S_{ii'}$ = the cost to the SPD of surgical groups i and i' having a block scheduled during the same time

D_i = maximum number of blocks surgical group i may have in a single block time

W_i = total number of blocks surgical group i is allocated during the planning horizon

a_s = weight given to SPD objective term (between 0 and 1)

Decision Variables:

Let x_{ijk} =

$\begin{cases} 1 & \text{if surgical group } i \text{ is assigned to OR } j \text{ during block time } k \\ 0 & \text{otherwise} \end{cases}$

Objective:

$$\begin{aligned} & \text{Min } (1 - a_s) \left(\sum_i \sum_j \sum_k \{P_{ijk} x_{ijk}\} \right) + a_s \left(\sum_k \left(\sum_j x_{1jk} [(\sum_j x_{1jk}) S_{1,1} + (\sum_j x_{2jk}) S_{1,2} + \dots (\sum_j x_{Ijk}) S_{1,I}] + \right. \right. \\ & \sum_j x_{2jk} [(\sum_j x_{2jk}) S_{2,2} + (\sum_j x_{3jk}) S_{2,3} + \dots (\sum_j x_{Ijk}) S_{2,I}] + \\ & \dots + \\ & \left. \left. \sum_j x_{Ijk} [(\sum_j x_{Ijk}) S_{I,I}] \right) \right) \end{aligned}$$

Subject to:

$$\sum_j x_{ijk} \leq D_i \quad \forall i, k \quad (1)$$

$$\sum_j \sum_k x_{ijk} = W_i \quad \forall i \quad (2)$$

$$\sum_i x_{ijk} = 1 \quad \forall j, k \quad (3)$$

$$x_{ijk} = \text{binary} \quad \forall i, j, k \quad (4)$$

The objective function minimizes the total sum of surgical group preferences cost and SPD cost. Recall that the parameters for surgical group preferences are an inverted Likert scale, which is why minimizing the first objective term actually maximizes preferences. The second objective term systematically checks all potential values in the workload matrix and adds them to the objective function only if the corresponding two surgical groups are assigned to that time period. This term does account for the possibility of a surgical group having more than one block in the same time period. The multiplication of binary decision variables results in a quadratic objective function. See appendix A for more information concerning the derivation of the second objective term.

The BAMQ constraints follow a typical assignment problem. Constraint (1) ensures that the total number of assigned blocks for a surgical group in a particular block time does not exceed the maximum allocated amount. Constraint (2) ensures that all surgical groups are given their exact number of allocated blocks during the planning horizon. Constraint (3) ensures every room is assigned a surgical group for each block time. Constraint (4) defines the decision variables as binary. All of the constraints are linear.

Section 4: S_{ij} Calculation Techniques

This research study examined four different calculation techniques for the S_{ij} parameter to examine their effectiveness and overall model robustness. If certain calculation techniques tend to perform better, then that will help researchers and practitioners looking to use the model because they will know which calculation techniques are more effective. Altering techniques also reveals if the

model is even sensitive to the calculation technique used. The $S_{ii'}$ parameter cannot equal the sum of the two C_i values because any feasible solution results in the same total SPD cost value. This is because of constraint (2). In other words, $S_{ii'} \neq C_i + C_i$ because the value for the total SPD cost would always equal $\sum_i C_i W_i$. Therefore, the $S_{ii'}$ parameter must be nonlinear.

The first calculation technique, known as the product technique, calculates $S_{ii'}$ as the product of the two surgical group cost terms:

$$S_{ii'} = C_i * C_i \quad 4.3$$

The product of two C_i terms is a simple equation that is easy to understand. Two groups with larger C_i values having the same block time will compound on one another much more than two groups with smaller C_i values.

The second calculation technique, known as the linear square technique, calculates $S_{ii'}$ as the square of the sum of the two surgical group cost terms:

$$S_{ii'} = (C_i + C_i)^2 \quad 4.4$$

The product of the sum of two C_i terms is also a simple equation that is easy to understand. Much like the product calculation technique, the linear square technique accounts for groups with larger C_i values having the same block time compounding much more than smaller groups. However, the linear square technique does this in a more aggressive manner than the product technique because the square of the sum of two numbers will be greater than their product for numbers greater than or equal to 1. Recall that all the C_i values are greater than 1.

The third calculation technique, known as the log technique, calculates $S_{ii'}$ as the log of the product of the two surgical group cost terms:

$$S_{ii'} = \log(C_i * C_i) \quad 4.5$$

The log calculation technique is not as intuitive as the product or linear square. However, the general effect is that the differences between smaller and larger surgical groups shrinks rather than compounds.

The fourth calculation technique, known as root mean square technique, calculates $S_{ii'}$ as the root mean square of the two surgical group cost terms:

$$S_{ii'} = \sqrt{\frac{C_i^2 + C_{i'}^2}{2}} \quad 4.6$$

Similar to the log technique, the root mean square is not as intuitive as the product or linear square and shrinks the differences between larger and smaller surgical groups rather than compounding.

After the $S_{ii'}$ vectors were calculated using one of the four techniques, they were scaled to a continuous 1-5 range using linear normalization. This was done to align the $S_{ii'}$ values with the Likert scale preferences values because it makes the actual weighting of the a_s parameter more intuitive. With the exception of the root mean square techniques, the $S_{ii'}$ values were significantly larger than the preferences parameters. In the most extreme case, the maximum $S_{ii'}$ value in the linear square technique was equal to 2,047,430.46. If the raw $S_{ii'}$ values were not scaled, then the preferences term in the objective function is essentially rendered obsolete unless the a_s parameter is virtually 0. Scaling the raw $S_{ii'}$ values also ensures consistent meaning for the a_s parameter across the four calculation techniques.

Section 5: BAMQ Evaluation Plan and Results

This research study conducted a systematic model evaluation plan to examine the effectiveness of the model and $S_{ii'}$ calculation techniques. Figure 8 illustrates the BAMQ evaluation plan. For each calculation technique, the model was run for 1 minute, 10 minutes, 1 hour, and 9 hours. The run times were selected to gauge the necessary length needed for an effective solution. The block assignment decision is generally made on an annual or bi-annual basis, meaning a 9-hour run time is not too long for practical applications. The a_s parameter ranged from 0.5 to 1, incrementing every 0.1. Thus, there were 24 runs for each calculation technique and 96 total runs.

The model was run using AMPL version 3.1 with CPLEX version 12.8 on a 64 bit 2.9GHz Intel Core Processor with 16.0 GB RAM using Microsoft Windows 10. The code used for the AMPL formulation is shown in Appendix A. A backup formulation of the problem was built in Microsoft Excel version 16 to validate the AMPL output. Parameter values were $i = 35$, $j = 7$, and $k = 5$ (five days, one block per OR per day).

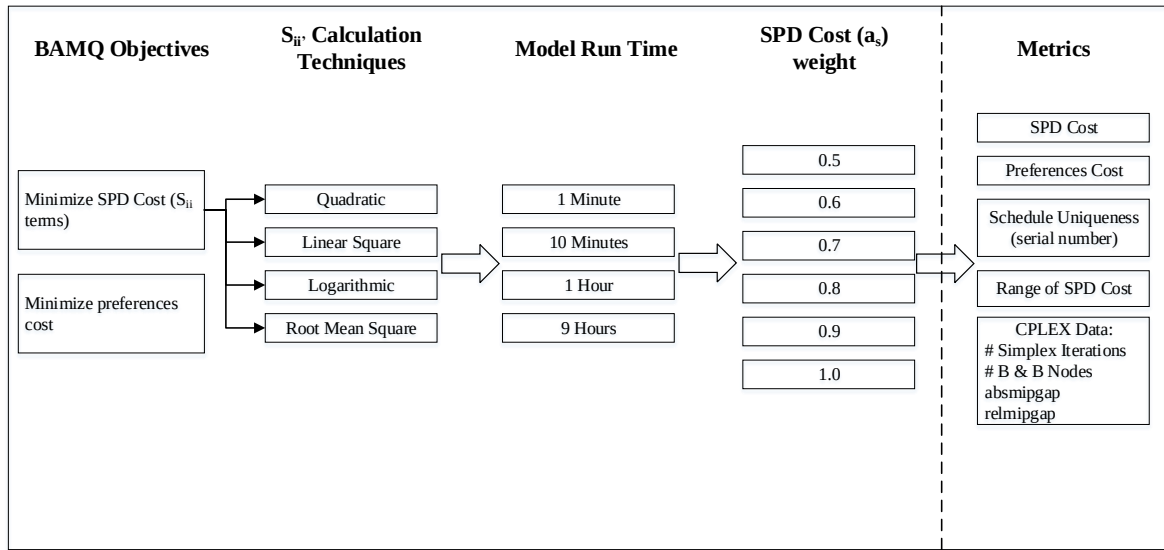


Figure 8: BAMQ Evaluation Plan

Several metrics were recorded for each run. These included the two objective terms, number of MIP Simplex Iterations, number of branch and bound nodes, the absolute MIP gap (absmipgap), and the relative MIP gap (relmipgap). The absmipgap refers to the absolute difference between the optimal integer solution and the optimal relaxed linear program solution. The relmipgap refers to the percentage difference between the optimal integer solution and the optimal relaxed linear program solution. The difference between the maximum SPD cost and minimum SPD cost of the five block times was also recorded to determine how even daily SPD caseload is throughout the week. This maximum daily caseload difference is referred to as “Range of SPD Cost” in the results tables. Additionally, each of the generated schedules was cross-checked against all other runs in the

evaluation plan to see how often the same schedule was created. The 96 model runs produced 21 unique schedules, referred to as “serial number” in the table.

Table 12 summarizes the model output for the BAMQ with product calculation technique. The current schedule for BHDH hospital is referred to as the “Baseline” schedule. For each a_s value, the baseline schedule results are shown for reference. Model run times are in seconds. The serial number column refers to whether the schedule generated by a particular a_s value – run time combination is unique. For example, the schedule generated by run times 60 and 600 for a_s value 0.8 were identical.

The BAMQ model with product technique improved upon the baseline objective schedule value in every instance. Run time did not affect the output until a_s was 0.8 or higher. The exact same schedule was generated for a_s values of 0.5, 0.6, and 0.7, regardless of run time. For this particular schedule, surgical group preferences were the same as the baseline schedule with a slight improvement in SPD cost. This was possible because surgical groups with multiple blocks had different C_i values for the different blocks but the same preferences. In other words, a surgical group with three allocated blocks would have three different C_i and was treated as three separated surgical groups for the i index in the BAMQ formulation. However, those three surgical groups had identical preferences because it was actually one group in practice. Thus, the model was able to better align different caseloads while still maintaining an optimal preferences value.

Once the a_s was 0.8 or higher, the model was more aggressive minimizing SPD cost and run time began to have an effect on performance. Not surprisingly, as the weight given to the SPD cost increased, the SPD cost improved at the expense of the preferences cost. However, the preferences cost did not dramatically suffer until the a_s value reached 1, meaning no weight was given to the preferences cost.

Table 12: BAMQ with Product Calculation Summary

Run Time (seconds)	a_s Weight	Objective Value	SPD Cost	Range of SPD Cost	Preference Cost	Serial Number	MIP Simplex Iterations	Branch and Bound Nodes	Absmipgap	Relmipgap
--	0.5	123.32	211.64	18.09	35	Baseline	--	--	--	--
60	0.5	122.82	210.64	18.13	35	1	6047	0	65.72	0.54
600	0.5	122.82	210.64	18.13	35	1	309542	602	64.74	0.53
3600	0.5	122.82	210.64	18.13	35	1	837205	3539	63.44	0.52
32400	0.5	122.82	210.64	18.13	35	1	7960702	43260	59.11	0.48
--	0.6	140.98	211.64	18.09	35	Baseline	--	--	--	--
60	0.6	140.38	210.64	18.13	35	1	7575	0	84.31	0.60
600	0.6	140.38	210.64	18.13	35	1	283005	897	82.26	0.59
3600	0.6	140.38	210.64	18.13	35	1	1202722	5211	78.91	0.56
32400	0.6	140.38	210.64	18.13	35	1	16848567	57746	71.13	0.51
--	0.7	158.648	211.64	18.09	35	Baseline	--	--	--	--
60	0.7	157.95	210.64	18.13	35	1	7518	0	101.05	0.64
600	0.7	157.95	210.64	18.13	35	1	347530	890	100.12	0.63
3600	0.7	157.95	210.64	18.13	35	1	1175713	4680	95.57	0.61
32400	0.7	157.95	210.64	18.13	35	1	16681086	59753	87.26	0.55
--	0.8	176.312	211.64	18.09	35	Baseline	--	--	--	--
60	0.8	175.23	208.04	9.47	44	3	7011	0	118.52	0.68
600	0.8	175.23	208.04	9.47	44	3	298748	816	118.14	0.67
3600	0.8	174.58	207.73	7.09	42	2	906433	3814	116.40	0.67
32400	0.8	174.58	207.73	7.09	42	2	6901196	55633	111.04	0.64
--	0.9	193.976	211.64	18.09	35	Baseline	--	--	--	--
60	0.9	191.51	207.46	5.19	48	6	6460	0	134.72	0.70
600	0.9	191.51	207.46	5.19	48	6	333132	1237	133.21	0.70
3600	0.9	191.96	207.73	7.15	50	7	905024	4109	134.37	0.70
32400	0.9	191.96	207.73	7.15	50	7	7883013	54226	130.68	0.68
--	1	211.64	211.64	18.09	35	Baseline	--	--	--	--
60	1	207.46	207.46	5.19	48	6	751	0	150.35	0.72
600	1	207.27	207.27	4.65	303	20	270137	2375	138.66	0.67
3600	1	207.35	207.35	5.59	200	11	1022854	9730	137.98	0.67
32400	1	207.19	207.19	3.15	200	17	13289504	151319	125.66	0.61

Figure 9 illustrates a positive correlation between the range of SPD Cost and the total SPD cost in the objective function. Recall the range of SPD cost is equal to the maximum daily SPD cost for the week minus the minimum daily SPD cost for the week. This value gives insight into how level the SPD workload is throughout the week. As the workload becomes more leveled, the total SPD cost decreases.

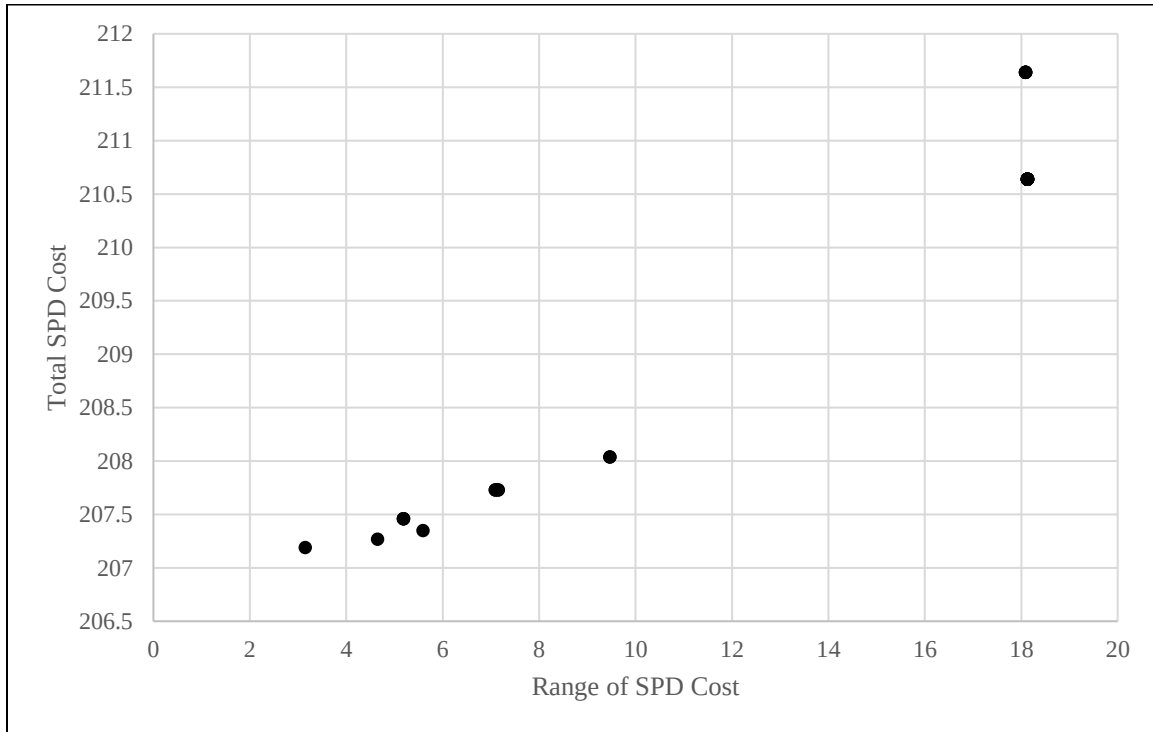


Figure 9: Range of SPD Cost vs. Total SPD Cost, Product Technique

Table 13 summarizes the model output for the BAMQ with linear square calculation. Note the similarities between the linear square calculation and product calculation results. The BAMQ with linear square calculation improved upon the baseline objective schedule value in every instance. The same schedule, serial number 1, which was generated by the product calculation a_s values of 0.5, 0.6, and 0.7, was generated by the linear square calculation a_s values of 0.5, 0.6, 0.7, and 0.8. Once the a_s value increased to 0.9, the model became more aggressive in reducing the SPD cost. However, run time only affected the output when the a_s was 1.

Table 13: BAMQ with Linear Square Calculation Summary

Run Time (seconds)	a_s Weight	Objective Value	SPD Cost	Range of SPD Cost	Preference Cost	Serial Number	MIP Simplex Iterations	Branch and Bound Nodes	Absmipgap	Relmipgap
--	0.5	127.52	220.03	21.15	35	Baseline	--	--	--	--
60	0.5	127.28	219.56	18.13	35	1	10914	0	69.044	0.542
600	0.5	127.28	219.56	18.13	35	1	232493	566	68.621	0.539
3600	0.5	127.28	219.56	18.13	35	1	761160	3138	67.418	0.53
32400	0.5	127.28	219.56	18.13	35	1	8661953	42007	63.664	0.5
--	0.6	146.02	220.03	21.15	35	Baseline	--	--	--	--
60	0.6	145.736	219.56	18.13	35	1	12599	0	87.739	0.602
600	0.6	145.736	219.56	18.13	35	1	367869	1247	87.193	0.598
3600	0.6	145.736	219.56	18.13	35	1	713338	3906	86.147	0.591
32400	0.6	145.736	219.56	18.13	35	1	7761361	47489	84.394	0.579
--	0.7	164.52	220.03	21.15	35	Baseline	--	--	--	--
60	0.7	164.192	219.56	18.13	35	1	12718	0	106.72	0.65
600	0.7	164.192	219.56	18.13	35	1	317653	743	106.43	0.648
3600	0.7	164.192	219.56	18.13	35	1	1050421	4247	105.05	0.64
32400	0.7	164.192	219.56	18.13	35	1	11062615	43887	99.949	0.609
--	0.8	183.02	220.03	21.15	35	Baseline	--	--	--	--
60	0.8	182.648	219.56	18.13	35	1	13373	0	125.66	0.688
600	0.8	182.648	219.56	18.13	35	1	285902	954	125.36	0.686
3600	0.8	182.648	219.56	18.13	35	1	860811	3236	123.92	0.678
32400	0.8	182.648	219.56	18.13	35	1	8786484	43930	119.41	0.654
--	0.9	201.53	220.03	21.15	35	Baseline	--	--	--	--
60	0.9	201.06	218.4	9.42	45	9	12359	0	143.74	0.715
600	0.9	201.06	218.4	9.42	45	9	347019	1200	143.71	0.715
3600	0.9	201.06	218.4	9.42	45	9	826812	3293	143.32	0.713
32400	0.9	201.06	218.4	9.42	45	9	8747853	55809	138.96	0.691
--	1	220.03	220.03	21.15	35	Baseline	--	--	--	--
60	1	218.07	218.07	5.29	306	19	1169	0	160.96	0.738
600	1	217.87	217.87	8.14	288	12	298731	2401	148.89	0.683
3600	1	217.8	217.8	7.94	303	16	1340830	9136	147.38	0.677
32400	1	217.8	217.8	7.94	303	16	9767576	71494	138.95	0.638

Figure 10 illustrates a similar positive correlation that occurred between the range of SPD cost and the total SPD cost. In summary, the linear square results closely followed the product results and produced the same schedule at lower a_s values. However, the differentiation between unique schedules did not occur until the run time and a_s were slightly higher than with the product calculation.

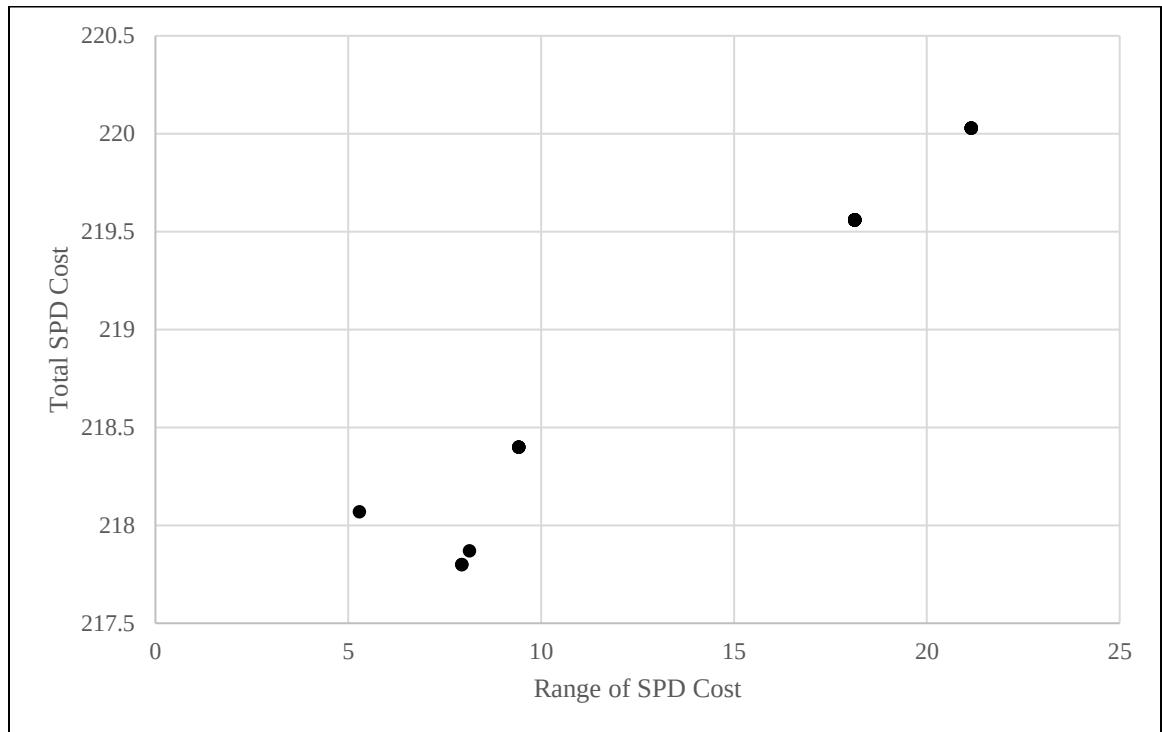


Figure 10: Range of SPD Cost vs. Total SPD Cost, Linear Square Technique

Table 14 displays the BAMQ with log calculation results. The same schedule, serial number one, is generated regardless of run time for a_s values 0.5 – 0.9. Only an a_s value of one produces unique schedules. Unlike the product and linear square results, the objective terms for the serial number one schedule is worse than the baseline, albeit by a small amount. However, the SPD cost does improve when the a_s value equals one. Furthermore, the range of SPD cost is improved in all but one run.

Table 14: BAMQ with Log Calculation Summary

Run Time (seconds)	a_s Weight	Objective Value	SPD Cost	Range of SPD Cost	Preference Cost	Serial Number	MIP Simplex Iterations	Branch and Bound Nodes	Absmipgap	Relmipgap
--	0.5	250.005	465.01	28.84	35	Baseline	--	--	--	--
60	0.5	250.02	465.04	18.13	35	1	6813	0	164.06	0.66
600	0.5	250.02	465.04	18.13	35	1	400646	1205	161.21	0.64
3600	0.5	250.02	465.04	18.13	35	1	892924	4007	159.86	0.64
32400	0.5	250.02	465.04	18.13	35	1	9850283	43884	151.02	0.60
--	0.6	293.006	465.01	28.84	35	Baseline	--	--	--	--
60	0.6	293.024	465.04	18.13	35	1	7577	0	201.16	0.69
600	0.6	293.024	465.04	18.13	35	1	306005	762	200.43	0.68
3600	0.6	293.024	465.04	18.13	35	1	969593	4043	198.26	0.68
32400	0.6	293.024	465.04	18.13	35	1	7576279	56127	191.5	0.65
--	0.7	336.007	465.01	28.84	35	Baseline	--	--	--	--
60	0.7	336.028	465.04	18.13	35	1	6839	0	238.59	0.71
600	0.7	336.028	465.04	18.13	35	1	301675	1090	236.48	0.70
3600	0.7	336.028	465.04	18.13	35	1	1223539	3100	235.74	0.70
32400	0.7	336.028	465.04	18.13	35	1	7206629	57719	227.28	0.68
--	0.8	379.008	465.01	28.84	35	Baseline	--	--	--	--
60	0.8	379.032	465.04	18.13	35	1	7242	0	275.04	0.73
600	0.8	379.032	465.04	18.13	35	1	368530	1251	274.13	0.72
3600	0.8	379.032	465.04	18.13	35	1	901018	3715	273.84	0.72
32400	0.8	379.032	465.04	18.13	35	1	9309547	42197	267.84	0.71
--	0.9	422.009	465.01	28.84	35	Baseline	--	--	--	--
60	0.9	422.036	465.04	18.13	35	1	6199	0	311.91	0.74
600	0.9	422.036	465.04	18.13	35	1	361988	1197	310.02	0.73
3600	0.9	422.036	465.04	18.13	35	1	1023907	3444	311.35	0.74
32400	0.9	422.036	465.04	18.13	35	1	13143181	41947	310.49	0.74
--	1	465.01	465.01	28.84	35	Baseline	--	--	--	--
60	1	465	465	19.16	197	10	722	0	348.73	0.75
600	1	464.92	464.92	58.23	298	13	304894	2436	324.78	0.70
3600	1	464.89	464.89	21.84	301	15	935110	8707	320.32	0.69
32400	1	464.89	464.89	21.84	301	15	7699352	76035	307.39	0.66

As shown in figure 11, the maximum daily caseload difference versus the SPD cost for log calculation differs from the product and linear square calculations. The log results show a weak negative correlation between maximum daily caseload and SPD cost. However, the range of the total SPD cost is only 0.15, making it difficult to draw any significant conclusions.

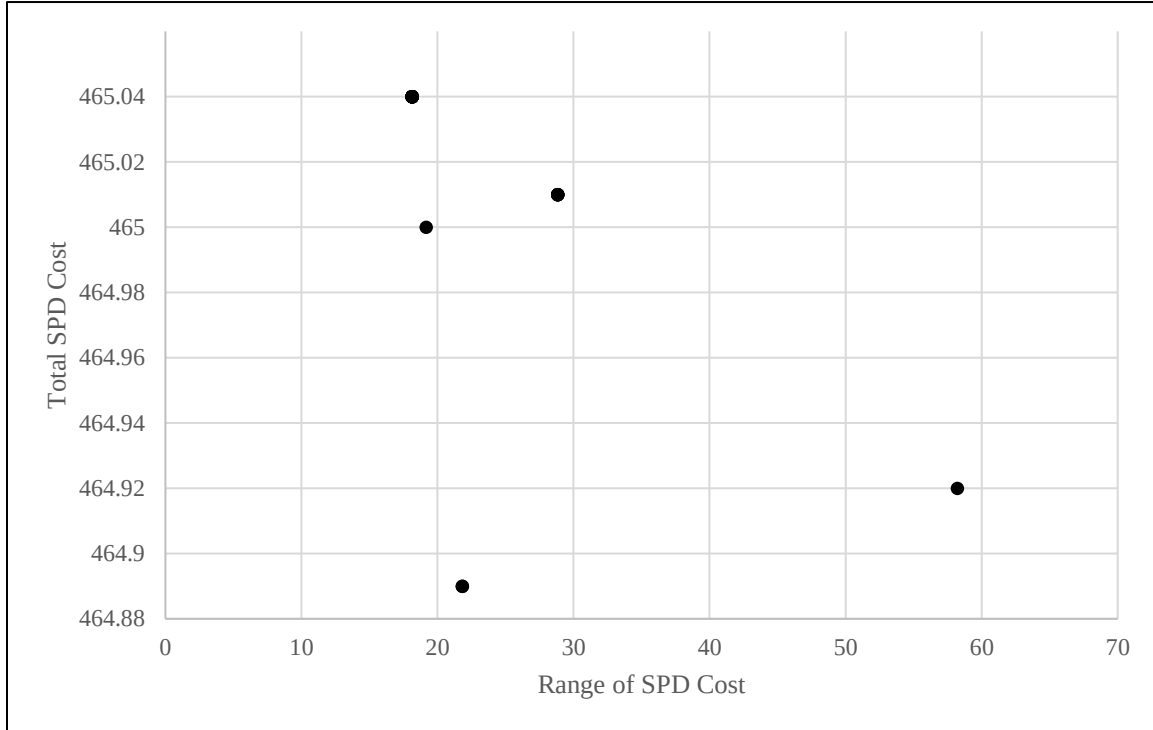


Figure 11: Range of SPD Cost vs. Total SPD Cost, Log Calculation

Table 15 displays the BAMQ with root mean square calculation results, which closely follow the log results. The same serial number one schedule is generated for a_s values 0.5 – 0.8 and for a_s value 0.9 with 60 second run time. For the serial schedule number one, the SPD cost and objective value are worse than the baseline. However, much like the log results, the range of SPD cost is still better than the baseline. A_s values of 0.9 (excluding the 60 second run time) and 1 improve upon the baseline SPD cost and overall objective value. Additionally, figure 12 shows a negative correlation between maximum daily caseload difference and SPD cost. This negative correlation appears to be stronger than the negative correlation in figure 11 (log calculation).

Table 15: BAMQ with Root Mean Square Calculation Summary

Run Time (seconds)	a_s Weight	Objective Value	SPD Cost	Range of SPD Cost	Preference Cost	Serial Number	MIP Simplex Iterations	Branch and Bound Nodes	Absmipgap	Relmipgap
--	0.5	179.105	323.21	29	35	Baseline	--	--	--	--
60	0.5	179.325	323.65	18.13	35	1	7358	0	112.37	0.627
600	0.5	179.325	323.65	18.13	35	1	226941	441	110.194	0.614
3600	0.5	179.325	323.65	18.13	35	1	924094	4331	108.473	0.605
32400	0.5	179.325	323.65	18.13	35	1	7380093	50273	102.261	0.570
--	0.6	207.926	323.21	29	35	Baseline	--	--	--	--
60	0.6	208.19	323.65	18.13	35	1	7013	0	139.323	0.669
600	0.6	208.19	323.65	18.13	35	1	158472	190	137.292	0.659
3600	0.6	208.19	323.65	18.13	35	1	1073017	4429	135.784	0.652
32400	0.6	208.19	323.65	18.13	35	1	8889780	59924	133.708	0.642
--	0.7	236.747	323.21	29	35	Baseline	--	--	--	--
60	0.7	237.055	323.65	18.13	35	1	6983	0	166.236	0.701
600	0.7	237.055	323.65	18.13	35	1	216205	568	164.684	0.695
3600	0.7	237.055	323.65	18.13	35	1	1073991	2782	163.601	0.690
32400	0.7	237.055	323.65	18.13	35	1	9428686	54546	156.907	0.662
--	0.8	265.568	323.21	29	35	Baseline	--	--	--	--
60	0.8	265.92	323.65	18.13	35	1	6592	0	192.308	0.723
600	0.8	265.92	323.65	18.13	35	1	189249	429	191.271	0.719
3600	0.8	265.92	323.65	18.13	35	1	1051864	2756	190.744	0.717
32400	0.8	265.92	323.65	18.13	35	1	10959886	44444	186.802	0.702
--	0.9	294.389	323.21	29	35	Baseline	--	--	--	--
60	0.9	294.785	323.65	18.13	35	1	6846	0	218.82	0.742
600	0.9	293.962	318.18	58.43	76	21	227501	542	217.7	0.741
3600	0.9	293.919	317.91	54.5	78	8	1027120	4458	217.38	0.740
32400	0.9	292.667	317.63	61.37	68	5	8356294	75675	208.164	0.711
--	1	323.21	323.21	29	35	Baseline	--	--	--	--
60	1	322.56	322.56	30.93	189	9	775	0	244.34	0.758
600	1	317.7	317.7	55.65	299	14	250088	2375	208.99	0.658
3600	1	315.99	315.99	59.43	304	18	1222857	7103	222.17	0.703
32400	1	315.99	315.99	59.43	304	18	18807170	148543	222.17	0.703

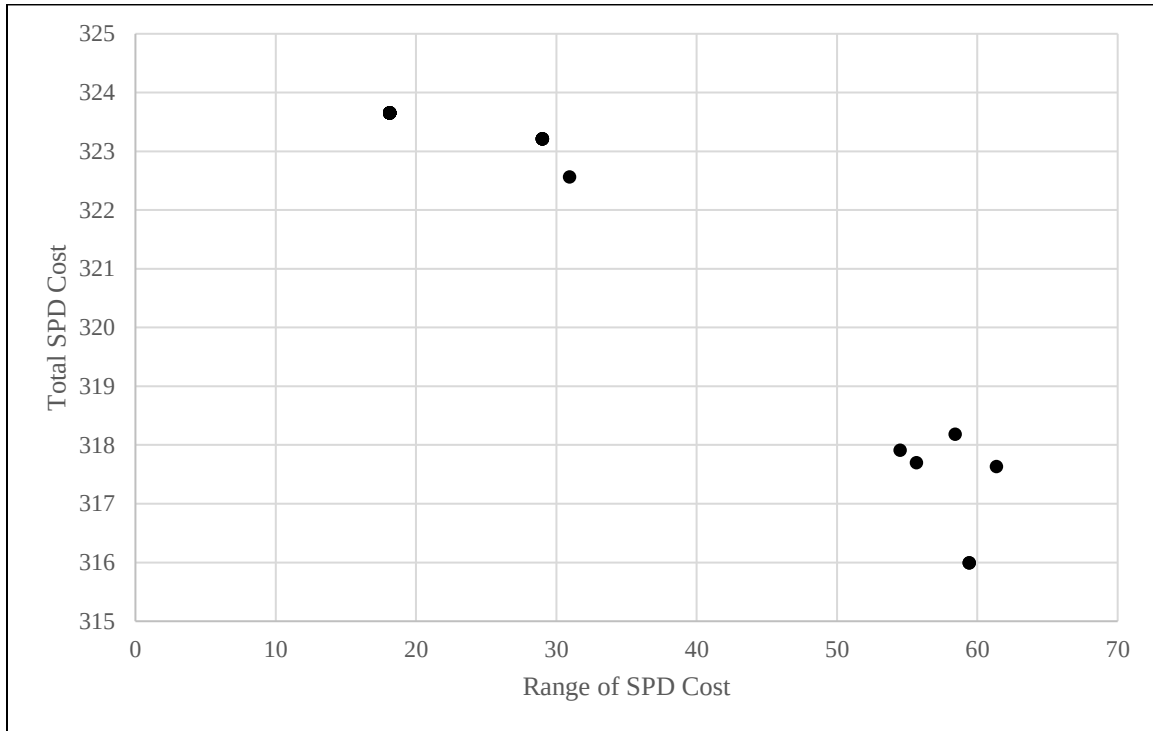


Figure 12: Range of SPD Costs vs. Total SPD Cost, Root Mean Square Calculation

Table 16 summarizes the key takeaways from the four different BAMQ product calculation techniques.

Table 16: BAMQ Results Summary

Calculation Technique	# Times (out of 24) Improve Upon Baseline Schedule	Range of SPD cost vs. Total SPD Cost	Schedules Differentiate
Product	24	Positive Correlation	a_s value > 0.7
Linear Square	24	Positive Correlation	a_s value > 0.8
Log	4	Weak Negative Correlation	a_s value = 1.0
Root Mean Square	7	Negative Correlation	a_s value > 0.8

The product and linear square calculation techniques outperform the log and root mean square techniques. Each of the 24 runs for product and linear square improve upon the baseline SPD cost and overall objective values. Conversely, the log and root mean square techniques only improve upon the baseline SPD cost and objective values in 4 and 7 runs, respectively. The positive

correlation between range of SPD cost and total SPD cost seen in the product and linear square techniques is more promising than the negative correlations seen in the log and root mean square techniques. A steady, level input into the SPD would seem to be better for the SPD than a more uneven input throughout the week. The product and linear square calculation techniques both compound instances where groups with higher caseloads have the same block time because of the quadratic nature of their formulas. This contrasts with the log and root mean square techniques, which tend to shrink the SPD cost in instances where groups with higher caseloads have the same block time. Tables 17-19 illustrate this concept. Table 17 displays the high-level summary for the historical baseline schedule. For each block time, the assigned surgical groups' C_i and preference is shown. For example, in block time $k = 1$, $j = 1$, the assigned surgical groups C_i value is 37.01 and its preference cost for that block time is 1.

Table 17: Baseline Schedule High Level Summary

		k				
		1	2	3	4	5
j	1	37.01 (1)	166.48 (1)	37.01 (1)	134.5 (1)	33.62 (1)
	2	86.21 (1)	553.85 (1)	219.69 (1)	217.81 (1)	149.71 (1)
	3	150.54 (1)	378.18 (1)	407.93 (1)	334.81 (1)	212.81 (1)
	4	287.95 (1)	289.2 (1)	405.03 (1)	150.54 (1)	168.58 (1)
	5	175.75 (1)	314.54 (1)	200.57 (1)	537.27 (1)	358.18 (1)
	6	103.99 (1)	205.38 (1)	715.44 (1)	150.21 (1)	142.57 (1)
	7	276.93 (1)	265.39 (1)	271.33 (1)	273.09 (1)	134.2 (1)
Total		1291.31 (7)	2173.02 (7)	2074.32 (7)	1798.32 (7)	1199.67 (7)

Table 18 displays the high-level summary for the schedule generated when a_s is 0.9, run time is 600, and the product calculation was used for S_{ii} . Table 19 displays the high-level summary for the schedule generated with the same a_s and run time, but with the root mean square calculation for S_{ii} . For the root mean square schedule, the surgical groups with the two highest C_i 's (715.44 and 553.85) are assigned the same block time k . Conversely, the product schedule is better at spreading out the

high C_i 's across different k 's. Additionally, the total C_i for each k in the product schedule is more even than the baseline schedule. The root mean square schedule, however, is more uneven across k than the baseline schedule.

Table 18: BAMQ Product, a_s 0.9, Run Time 600 Schedule High Level Summary

		k				
		1	2	3	4	5
j	1	37.01 (1)	166.48 (1)	33.62 (3)	37.01 (3)	149.71 (2)
	2	265.39 (1)	334.81 (1)	175.75 (1)	217.81 (1)	134.5 (5)
	3	150.54 (1)	378.18 (1)	276.93 (1)	212.81 (1)	553.85 (1)
	4	405.03 (1)	314.54 (2)	715.44 (2)	168.58 (1)	150.54 (1)
	5	219.69 (1)	289.2 (2)	200.57 (1)	537.27 (1)	358.18 (1)
	6	103.99 (1)	205.38 (1)	287.95 (2)	271.33 (1)	142.57 (1)
	7	407.93 (1)	134.2 (1)	150.21 (1)	86.21 (1)	273.09 (1)
Total		1589.58 (7)	1822.79 (9)	1840.47 (11)	1531.02 (9)	1762.44 (12)

Table 19: BAMQ Root Mean Square, a_s 0.9, Run Time 600 Schedule High Level Summary

		k				
		1	2	3	4	5
j	1	37.01 (3)	134.5 (3)	405.03 (3)	149.71 (2)	378.18 (2)
	2	103.99 (3)	150.54 (1)	715.44 (3)	219.69 (3)	217.81 (1)
	3	33.62 (4)	166.48 (3)	334.81 (1)	168.58 (2)	212.81 (1)
	4	150.54 (1)	175.75 (4)	553.85 (2)	287.95 (1)	200.57 (3)
	5	37.01 (3)	537.27 (3)	358.18 (3)	276.93 (2)	314.54 (3)
	6	86.21 (3)	150.21 (1)	407.93 (2)	205.38 (1)	142.57 (1)
	7	134.2 (2)	289.2 (2)	271.33 (1)	265.39 (1)	273.09 (1)
Total		582.58 (19)	1603.95 (18)	3046.57 (15)	1573.63 (12)	1739.57 (12)

The BAMQ results suggest that having a quadratic element to the $S_{ii'}$ formula achieves better results than non-quadratic elements such as log or square root. Intuitively, the model should avoid scenarios where the surgical groups with the highest C_i 's have the same block time. Linear square, quadratic, or other similar formulas such as cubing the sum of two C_i are recommended for future applications of the model. The product and linear square calculation techniques start to produce

unique schedules at a_s values of 0.8 and 0.9, respectively. The results are relatively robust to run time at these a_s values, which is useful for practical application.

Section 6: BAMLGPD

The BAMQ linear square and product results indicated a positive correlation between range of SPD cost and total SPD cost. A second model, referred to as Block Assignment Model Linear Goal Programming Deviation (BAMLGPD), more directly addresses the range of SPD cost. The BAMLGPD operates under the same background and assumptions as BAMQ. The BAMLGPD is formulated as follows:

Parameters:

P_{ijk} = preferences for surgical group i ($i = 1, 2, \dots, I$) to have OR j ($j = 1, 2, \dots, J$) during block time k ($k = 1, 2, \dots, K$)

C_i = average total time for the SPD to manually process the daily caseload of surgical group i

D_i = maximum number of blocks each group may have in a single block time

W_i = total number of blocks each group is allocated during the planning horizon

a_s = weight given to SPD/Materials (between 0 and 1)

Decision Variables:

Let x_{ijk} =

$$\begin{cases} 1 & \text{if surgical group } i \text{ is assigned to OR } j \text{ during block time } k \\ 0 & \text{otherwise} \end{cases}$$

Let s_k^- = amount the total daily caseload on day k is under the average total daily caseload

Let s_k^+ = amount the total daily caseload on day k is over the average total daily caseload

Objective:

$$\text{Min } (1 - a_s) \left(\sum_i \sum_j \sum_k \{P_{ijk} x_{ijk}\} \right) + a_s \left(\sum_k \{s_k^- + s_k^+\} \right)$$

Subject to:

$$\sum_j x_{ijk} \leq D_i \quad \forall i, k \quad (1)$$

$$\sum_j \sum_k x_{ijk} = W_i \quad \forall i \quad (2)$$

$$\sum_i x_{ijk} = 1 \quad \forall j, k \quad (3)$$

$$\sum_i \sum_j \{x_{ijk} * C_i\} + s_k^- - s_k^+ = \frac{\sum_i C_i W_i}{K} \quad \forall k \quad (4)$$

$$x_{ijk} = \text{binary} \quad \forall i, j, k \quad (5)$$

$$s_k^-, s_k^+ \geq 0 \quad \forall k \quad (6)$$

Similar to BAMQ, the objective function minimizes the total sum of surgical group preferences and SPD cost. However, SPD cost is calculated differently. With BAMLGPD, the second objective term minimizes the total SPD caseload deviation from the overall average SPD caseload for each time period. Goal programming is used for this objective term because of its ability to capture deviation from the mean. This formulation results in a linear objective function.

The BAMLGPD constraints follow the BAMQ constraints, with the addition of constraints (4) and (6). Constraint (1) ensures that the total number of assigned blocks for a surgical group in a particular block time does not exceed the maximum allocated amount. Constraint (2) ensures that all surgical groups receive their number of allocated blocks during the planning horizon. Constraint (3) ensures every room has a surgical group for each block time. Constraint (4) relates the deviation variables s_k^- and s_k^+ to the total average SPD caseload. Constraint (4) is a goal programming technique. The objective is to make the total SPD cost for each time period equal to one another. This equality constraint makes feasibility incredibly difficult. Therefore, two variables representing the overage and underage for each block time are created and minimized in the objective function. Constraint (5) defines the decision variables as binary. Constraint (6) ensures each deviation term is nonnegative. All constraints are linear.

Section 7: 2 Phase BAMLGPD

This research study also examined a two-phased version of the BAMLGPD, known as 2BAMLGPD. The intent of the 2BAMLGPD was to reduce computational complexity of BAMLGPD by splitting the model into two phases. In the first phase, the 2BAMLGPD minimizes only the SPD cost while not considering the OR (j index) decision. In other words, phase one assigns surgical groups to block times but not ORs within the block times. The only concern in phase one is minimizing SPD cost. Phase two takes the output of phase one as a constraint and assigns surgical groups to ORs within their allocated block time. Phase two minimizes the preferences cost. Essentially, the first phase of 2BAMLGPD decides which surgical groups are assigned to a particular block time (minimizing BAMLGPD SPD cost) and the second phases assigns the surgical groups to an OR within the block time (minimizing preferences cost). Phase one 2BAMLGPD is formulated as follows:

Parameters:

C_i = average total time for the SPD to manually process the daily caseload of surgical group i

D_i = maximum number of blocks each group may have in a single block time

W_i = total number of blocks each group is allocated during the planning horizon

Decision Variables:

Let x_{ik} = number of ORs surgical group i is assigned during block time k

Let s_k^- = amount the total daily caseload on day k is under the average total daily caseload

Let s_k^+ = amount the total daily caseload on day k is over the average total daily caseload

Objective:

$$\text{Min } (\sum_k \{s_k^- + s_k^+\})$$

Subject to:

$$x_{ik} \leq D_i \quad \forall i, k \quad (1)$$

$$\sum_k x_{ik} = W_i \quad \forall i \quad (2)$$

$$\sum_i x_{ik} = J \quad \forall k \quad (3)$$

$$\sum_i \{x_{ik} * C_i\} + s_k^- - s_k^+ = \frac{\sum_i C_i W_i}{K} \quad \forall k \quad (4)$$

$$x_{ik} = integer \quad \forall i, k \quad (5)$$

$$s_k^-, s_k^+ \geq 0 \quad \forall k \quad (6)$$

The phase one 2BAMLGPD objective minimizes the total SPD costs. It is a linear objective. The 2BAMLGPD phase one constraints are similar to the BAMLGPD constraints. Constraint (1) ensures that the total number of assigned blocks for a surgical group in a particular block time does not exceed the maximum allocated amount. Constraint (2) ensures that all surgical groups receive their exact number of allocated blocks during the planning horizon. Constraint (3) ensures the total number of assigned blocks for each block time is equal to the number of ORs in the OR suite. Constraint (4) relates the deviation variables s_k^- and s_k^+ to the total average SPD caseload. Constraint (5) defines the decision variables as integer. In this research study, x_{ik} became binary because a surgical group with multiple block allocations were treated as separate i . In other words, $D_i = 1 \forall i$. Constraint (6) ensures each deviation term is nonnegative. All of the constraints are linear.

Once the first phase is solved, the second phase of 2BAMLGPD minimizes the preferences cost given the output from the first phase. The second phase is formulated as:

Parameters:

P_{ijk} = preferences for surgical group i ($i = 1, 2, \dots, I$) to have OR j ($j = 1, 2, \dots, J$) during block time k ($k = 1, 2, \dots, K$)

x_{ik} = number of ORs surgical group i is assigned during block time k in phase one

Decision Variables:

Let y_{ijk} =

$$\begin{cases} 1 & \text{if surgical group is assigned to OR } j \text{ during block time } k \\ 0 & \text{otherwise} \end{cases}$$

Objective:

$$\text{Min } \sum_i \sum_j \sum_k (P_{ijk} y_{ijk})$$

Subject to:

$$\sum_j y_{ijk} = x_{ik} \quad \forall i, k \quad (1)$$

$$\sum_i y_{ijk} = 1 \quad \forall j, k \quad (2)$$

$$y_{ijk} = \text{binary} \quad \forall i, j, k \quad (3)$$

Constraint (1) links the phase one output to the phase two formulation. The number of ORs a surgical group has in a time period is equal to the phase one solution. Constraint (2) ensures each OR has a surgical group for every block time. Constraint (3) defines the decision variables as binary.

Section 8: BAMLGPD, 2BAMLGPD Evaluation Plan and Results

The BAMLGPD evaluation plan was similar to BAMQ with the exception of $S_{ii'}$ calculation techniques. The BAMLGPD evaluation plan had a similar objective of examining the effect (if any) run time and a_s weight had on solution quality. Figure 13 displays the BAMLGPD evaluation plan and figure 14 displays the 2BAMLGPD evaluation plan. The two-phase aspect of 2BAMLGPD limited the evaluation plan to altering run times only because addressing SPD cost deviation first means the a_s weight equals one.

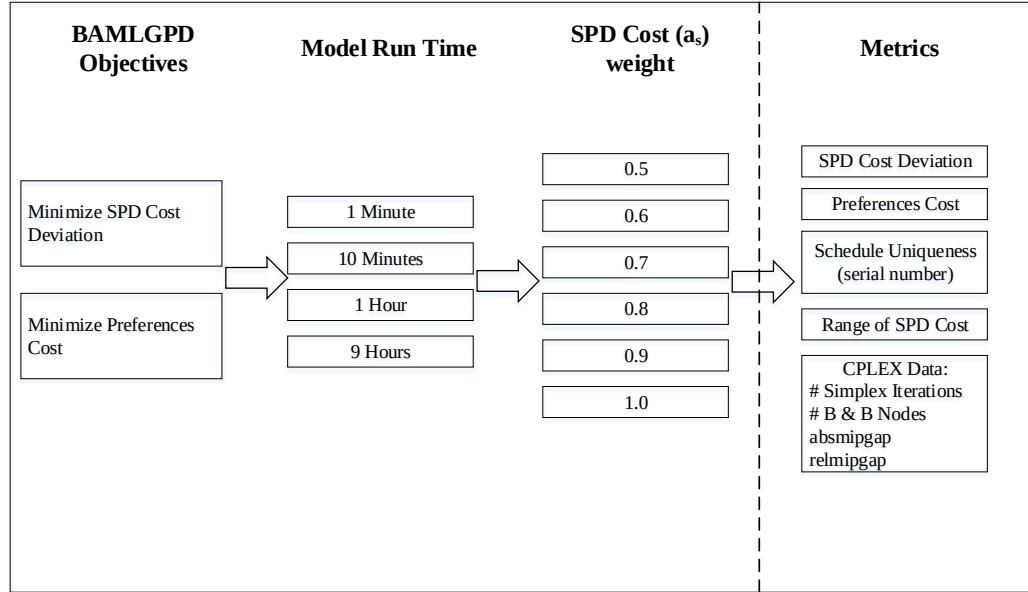


Figure 13: BAMLGPD Evaluation Plan

For BAMLGPD, a_s values of 0.5 – 1 incrementing every 0.1 were run for 60, 600, 3600, and 32400 seconds. Thus, there were 24 total runs. The model was run using AMPL version 3.1 with CPLEX version 12.8 on a 64 bit 2.9GHz Intel Core Processor with 16.0 GB RAM using Microsoft Windows 10. Appendix A displays the AMPL code. A backup formulation of the problem was built in Microsoft Excel version 16 to validate the AMPL output.

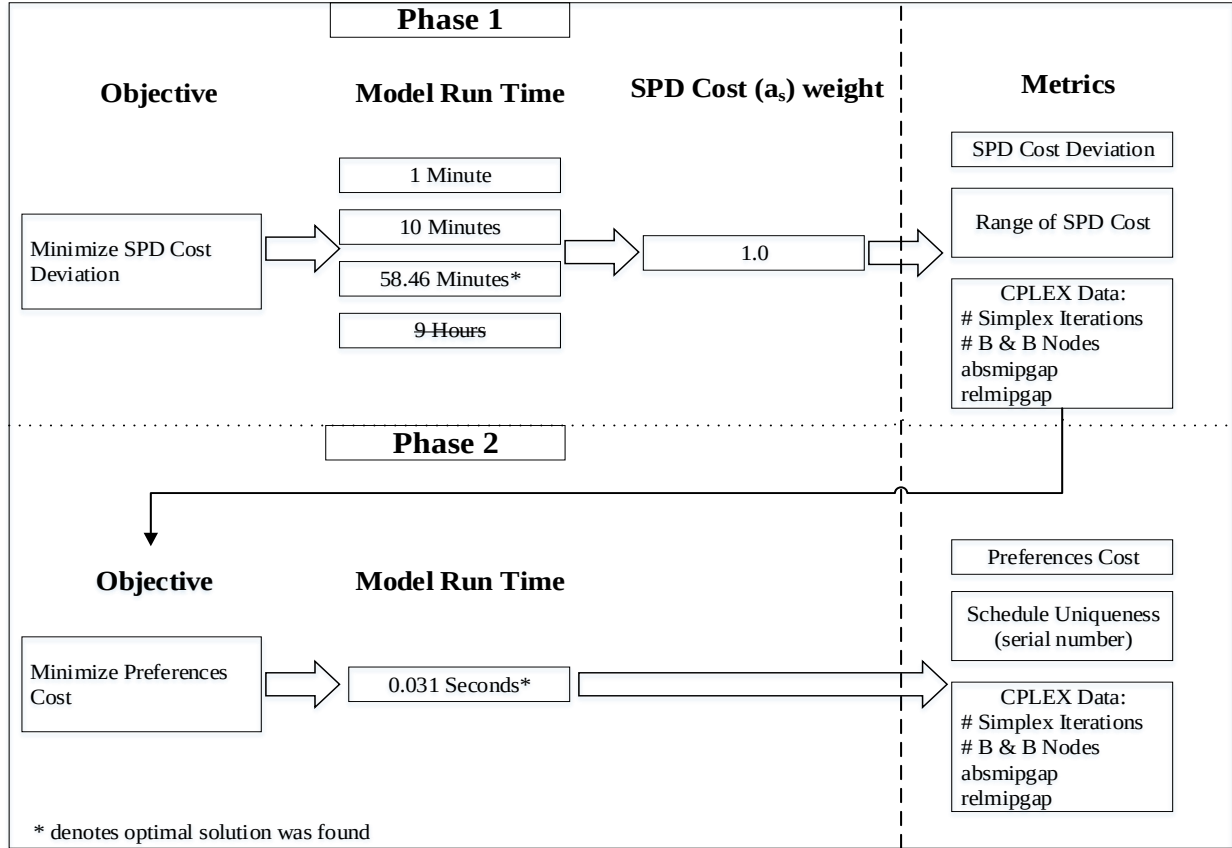


Figure 14: 2BAMLGPD Evaluation Plan

Parameter values were $i = 35$, $j = 7$, and $k = 5$ (five days, one block per OR per day). CPLEX found an optimal solution to 2BAMLGPD phase 1 in 3507.86 seconds, or just under 1 hour. Therefore, a nine-hour run was unnecessary. Additionally, when CPLEX was given a 60 second and 600 second run time, it still found the same optimal solution, though it was unable to verify optimality. CPLEX found an optimal solution to 2BAMLGPD phase two in 0.031 seconds. The phase two objective value was 71. Table 20 displays the BAMLGPD and 2BAMLGPD results. In the simplex iterations and branch and bound node 2BAMLGPD columns, the first line is phase one and the second line is phase two. A serial number of “Base” refers to how the historical baseline schedule performs in the formulation. The SPD Cost Deviation and Range of SPD Cost values are in minutes because there was no scaling involved with the C_i parameters.

Table 20: BAMLGPD and 2BAMLGPD Results

Model	Run Time (seconds)	a_s Weight	Objective Value	SPD Cost Deviation (min)	Range of SPD Cost (minutes)	Preference Cost	Serial Number	MIP Simplex Iterations	Branch and Bound Nodes	Absmipgap	Relmipgap
BAMLGPD	--	0.5	1118	2201	1139	35	Base	--	--	--	--
BAMLGPD	60	0.5	25.32	8.64	4.87	42	22	1322578	247506	7.09	0.28
BAMLGPD	600	0.5	22.22	1.44	0.99	43	23	5957718	938156	3.56	0.16
BAMLGPD	3600	0.5	22.22	1.44	0.99	43	23	26809670	3513174	3.03	0.14
BAMLGPD	32400	0.5	22.22	1.44	0.99	43	23	309895674	28906640	1.72	0.08
BAMLGPD	--	0.6	1334.6	2201	1139	35	Base	--	--	--	--
BAMLGPD	60	0.6	21.8	7	4.87	44	24	1264272	231552	6.91	0.32
BAMLGPD	600	0.6	18.06	1.44	0.99	43	23	6420797	931060	2.63	0.15
BAMLGPD	3600	0.6	18.06	1.44	0.99	43	23	30671979	3409688	2.56	0.14
BAMLGPD	32400	0.6	18.06	1.44	0.99	43	23	334889635	30152880	1.81	0.10
BAMLGPD	--	0.7	1551.2	2201	1139	35	Base	--	--	--	--
BAMLGPD	60	0.7	16.088	2.84	1.6	47	25	1416694	204510	4.71	0.29
BAMLGPD	600	0.7	13.908	1.44	0.99	43	23	8282270	932496	2.15	0.15
BAMLGPD	3600	0.7	13.908	1.44	0.99	43	23	31244318	3806959	1.78	0.13
BAMLGPD	32400	0.7	13.908	1.44	0.99	43	23	331213411	33498305	1.01	0.07
BAMLGPD	--	0.8	1767.8	2201	1139	35	Base	--	--	--	--
BAMLGPD	60	0.8	11.072	1.34	0.79	50	26	1245269	175491	3.48	0.31
BAMLGPD	600	0.8	9.752	1.44	0.99	43	23	6025112	902740	1.91	0.20
BAMLGPD	3600	0.8	9.752	1.44	0.99	43	23	25142779	3625300	1.74	0.18
BAMLGPD	32400	0.8	9.752	1.44	0.99	43	23	274815313	29229974	1.49	0.15
BAMLGPD	--	0.9	1984.4	2201	1139	35	Base	--	--	--	--
BAMLGPD	60	0.9	6.206	1.34	0.79	50	26	1282802	189214	2.48	0.40
BAMLGPD	600	0.9	5.596	1.44	0.99	43	23	6830507	842484	1.83	0.33
BAMLGPD	3600	0.9	5.432	0.48	0.4	50	27	27436565	3324802	1.58	0.29
BAMLGPD	32400	0.9	5.432	0.48	0.4	50	27	194659013	28107703	1.30	0.24
BAMLGPD	--	1	323.21	2201	1139	35	Base	--	--	--	--
BAMLGPD	60	1	0.66	0.66	0.5	70	28	1573569	335948	0.66	1
BAMLGPD	600	1	0.14	0.14	0.13	295	29	10349360	2319565	0.14	1
BAMLGPD	3600	1	0.04	0.04	0.03	209	30	69239102	14247225	0.04	1
BAMLGPD	32400	1	0.02	0.02	0.02	199	31	421116506	95614942	0.02	1
2BAMLGPD	60	1		0.02	0.02	71	32	1754783 14	683178 0	0.02	1
2BAMLGPD	600	1		0.02	0.02	71	32	20938141 14	5308188 0	0.02	1
2BAMLGPD	3507.86	1		0.02	0.02	71	32	125870245 14	30192985 0	0	0

The BAMLGPD results improved upon the baseline schedule objective value in every instance. The relative magnitude of improvement was much larger than BAMQ. The linear formulation of BAMLGPD likely accounts for the larger number of simplex iterations and branch and bodes than in the BAMQ results. BAMLGPD had several instances in which the same schedule was generated across different a_s values and run times, though this did not occur as frequently as BAMQ. As the a_s weight increased, model run time began to have more of an effect. The nine-hour run time improved upon the one hour run time once (a_s value equals one), which suggest an hour is sufficient. Figure 15 displays the BAMLGPD maximum daily caseload difference (range of SPD cost) versus total SPD cost. Much like the BAMQ product and linear square results, a positive correlation occurs.

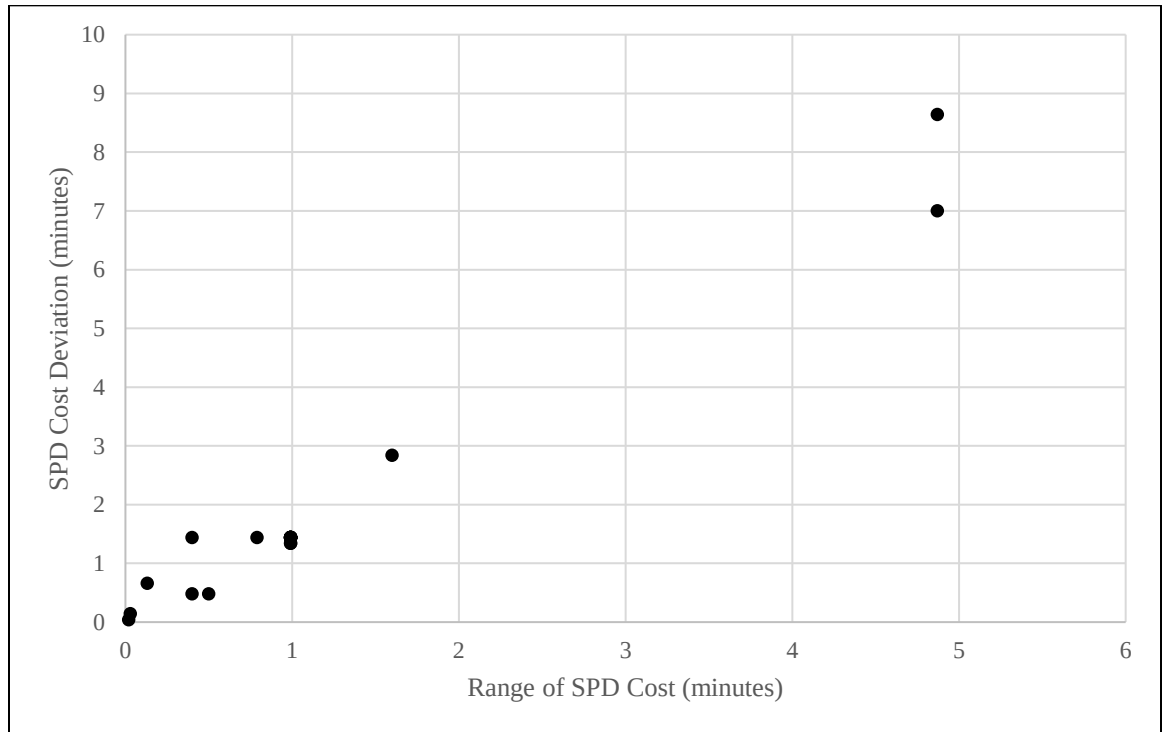


Figure 15: BAMLGPD Range of SPD Cost vs. SPD Cost Deviation

Separating BAMLGPD into two phases dramatically reduces the time needed for CPLEX to find the optimal solution. However, the tradeoff is that the natural balancing between the potentially conflicting SPD cost and surgical group preferences objectives is lost. This results in an ideal SPD

cost at the possible expense of surgical group preferences. When the BAMLGPD a_s weight is one, the 2BAMLGPD solves the problem more efficiently. This result makes sense, because the same problem is being addressed with fewer decision variables because there is no OR (j) index. Thus, the 2BAMLGPD could be used as a lower bound for the SPD cost term to compare when using BAMLGPD. An opportunity for future research is to apply the 2BAMLGPD and use hard constraints in the first phase to factor in select preferences that are important to surgical groups.

Section 9: Comparison of BAMQ and BAMLGPD

BAMLGPD is the more effective model in terms of improving upon the baseline schedule objective value. BAMLGPD is a cleaner formulation of the problem and its linear nature allows solvers to explore more branch and bound nodes in the same run time. An additional way to compare model effectiveness is to examine how well the schedule generated by one model performs in the other model's formulation. In other words, if the schedule generated by BAMLGPD a_s value 0.5 run time 60 is substituted into the BAMQ LS formulation, how would the objective value compare to the original BAMQ LS a_s value 0.5 run time 60 schedule, and vice versa?

Tables 21 displays how the BAMLGPD schedules compare to the BAMQ LS schedules in the BAMQ LS formulation. For example, when the schedule generated by BAMLGPD a_s weight 0.5 run time 60 was substituted into the BAMQ LS formulation, it had an objective value of 129.92. Obviously, the preferences cost term (42) was the same because that does not differ in the BAMQ LS and BAMLGPD formulations. However, the SPD cost term changed from 8.64 (total daily SPD cost deviation from the overall average) to 217.83 (the sum of all the possible S_{iij} terms). This compares to a preferences cost of 35 and SPD cost of 219.56 respectively, for the actual schedule generated by BAMQ LS for those a_s and run time parameters. As Table 21 shows, the BAMLGPD schedules are quite close to the BAMQ LS objective values. In certain instances, the BAMLGPD schedules

outperform the BAMQ LS schedules, even though those schedules were intended to minimize a different objective function.

Table 21: BAMLGPD in BAMQ LS Formulation

		BAMQ LS			BAMLGPD in BAMQ LS Formulation		
Run Time	a_s Weight	Objective Value	SPD Cost (minutes)	Preference Cost	Objective Value	SPD Cost (minutes)	Preference Cost
60	0.5	127.28	219.56	35	129.92	217.83	42
600	0.5	127.28	219.56	35	130.375	217.75	43
3600	0.5	127.28	219.56	35	130.375	217.75	43
32400	0.5	127.28	219.56	35	130.375	217.75	43
60	0.6	145.736	219.56	35	148.286	218.81	44
600	0.6	145.736	219.56	35	147.85	217.75	43
3600	0.6	145.736	219.56	35	147.85	217.75	43
32400	0.6	145.736	219.56	35	147.85	217.75	43
60	0.7	164.192	219.56	35	166.56	217.8	47
600	0.7	164.192	219.56	35	165.325	217.75	43
3600	0.7	164.192	219.56	35	165.325	217.75	43
32400	0.7	164.192	219.56	35	165.325	217.75	43
60	0.8	182.648	219.56	35	184.264	217.83	50
600	0.8	182.648	219.56	35	182.8	217.75	43
3600	0.8	182.648	219.56	35	182.8	217.75	43
32400	0.8	182.648	219.56	35	182.8	217.75	43
60	0.9	201.06	218.4	45	184.264	217.83	50
600	0.9	201.06	218.4	45	200.275	217.75	43
3600	0.9	201.06	218.4	45	200.975	217.75	50
32400	0.9	201.06	218.4	45	200.975	217.75	50
60	1	218.07	218.07	306	217.82	217.82	70
600	1	217.87	217.87	288	217.86	217.86	295
3600	1	217.8	217.8	303	217.86	217.86	209
32400	1	217.8	217.8	303	217.79	217.79	199

Table 22 displays how the BAMQ LS schedules perform in the BAMLGPD formulation.

The BAMQ LS schedules do not perform well in the BAMLGPD formulation. The objective value is

often more than 100 times worse than the BAMLGPD schedule. However, the BAMQ LS schedules still outperform the baseline schedule in the BAMLGPD formulation. Recall that the baseline BAMLGPD schedule yielded a preferences cost of 35 and SPD cost of 2200.94.

Table 22: BAMQ LS in BAMLGPD Formulation

		BAMLGPD			BAMQ LS in BAMLGPD Formulation		
Run Time	a_s Weight	Objective Value	SPD Cost (minutes deviation)	Preference Cost	Objective Value	SPD Cost (minutes deviation)	Preference Cost
60	0.5	25.319	8.64	42	932.79	1830.58	35
600	0.5	22.22	1.44	43	932.79	1830.58	35
3600	0.5	22.22	1.44	43	932.79	1830.58	35
32400	0.5	22.22	1.44	43	932.79	1830.58	35
60	0.6	21.8	7	44	1112.348	1830.58	35
600	0.6	18.064	1.44	43	1112.348	1830.58	35
3600	0.6	18.064	1.44	43	1112.348	1830.58	35
32400	0.6	18.064	1.44	43	1112.348	1830.58	35
60	0.7	16.088	2.84	47	1291.906	1830.58	35
600	0.7	13.908	1.44	43	1291.906	1830.58	35
3600	0.7	13.908	1.44	43	1291.906	1830.58	35
32400	0.7	13.908	1.44	43	1291.906	1830.58	35
60	0.8	11.072	1.34	50	1471.464	1830.58	35
600	0.8	9.752	1.44	43	1471.464	1830.58	35
3600	0.8	9.752	1.44	43	1471.464	1830.58	35
32400	0.8	9.752	1.44	43	1471.464	1830.58	35
60	0.9	6.206	1.34	50	945.918	1046.02	45
600	0.9	5.596	1.44	43	945.918	1046.02	45
3600	0.9	5.432	0.48	50	945.918	1046.02	45
32400	0.9	5.432	0.48	50	945.918	1046.02	45
60	1	0.66	0.66	70	686.24	686.24	306
600	1	0.14	0.14	295	358.1	358.1	288
3600	1	0.04	0.04	209	219.9	219.9	303
32400	1	0.02	0.02	199	219.9	219.9	303

The results in tables 21 and 22 suggest BAMLGPD is a better model because the schedules generated by BAMLGPD still do quite well in the BAMQ formulation. This is likely due to two reasons. First, the BAMLGPD more directly addresses the positive correlation seen between range of SPD cost and total SPD cost. BAMLGPD minimizes the total daily caseload deviation from the overall average, which is closely related to range of SPD cost. Second, BAMLGPD is linear. The computational complexity is not as high as BAMQ, which has quadratic terms in the objective function. A final advantage BAMLGPD has over BAMQ is in its simplicity. The BAMQ's effectiveness depends in part on the calculation method used for the $S_{ii'}$ terms. BAMLGPD does not have this issue.

Section 10: Limitations and Future Research

The block assignment models in this chapter do have limitations. The models apply only to OR suites that follow a block schedule. The relative MIP gap for the BAMQ and select BAMLGPD results is large and requires further examination. For example, would longer model run times reduce these gaps? The problem size the models can manage in a realistic run time may be limited. The models do not address OR case arrival timing to the SPD. In other words, the expected end time of surgical cases and their arrival into the SPD during the day is not considered.

The model limitations affect the interpretation of the results. None of the models in this chapter generalize to OR suites that utilize an open or modified block scheduling system. While the BAMQ with product or linear square techniques and BAMLGPD improved over the baseline schedule, it is difficult to generalize that this will always be the case. The details of the surgical groups' caseloads and preferences likely play a role in how much the models can improve upon the baseline. In other words, if the models were applied to a scenario where there is not much difference in the surgical groups' caseloads (C_i), then the models may not be able to improve much because the

schedule will always be relatively even across the planning horizon. Finally, the large relative MIP gap means it is difficult to discern how large the problem size can become before the models cannot provide good results.

Areas for future research surround addressing the models' limitations. The assumption of consistent SPD staffing throughout the model time horizon could be relaxed. Researchers could also explore how to reduce the relative MIP gaps through longer run times, heuristics, or altering the models. The relationship between the size of the problem (number of surgical groups, ORs, and time blocks) and solution quality (relative MIP gap) could be systematically explored. Extending the models to open or modified block settings would be an interesting challenge for researchers. Finally, the dynamic between the distribution of surgical group caseloads and amount the models improve upon the baseline could be systematically explored.

Section 11: Chapter Summary

The first research hypothesis of this study was a mathematical OR scheduling model that incorporates SPD impact can improve SPD performance. This chapter presented a series of mathematical models, BAMQ, BAMLGPD, and 2BAMLGPD, which assign surgical groups block time while minimizing changes to the current schedule and expected SPD processing time. Incorporating a block schedule's impact on the SPD into an objective function that also considers surgical group preferences is what makes these models unique from previous OR scheduling models. The block assignment models generalize to any OR suite that follows a block schedule and has a SPD service its instruments in a parallel process relationship (meaning the SPD services instruments while the OR is performing surgeries).

For each model, an evaluation plan was conducted to examine how altering parameters such as model run time, objective term weights, and SPD cost parameter calculation techniques (BAMQ only) impact solution quality and uniqueness. Several key takeaways emerged:

- The BAMQ is sensitive to S_{ij} calculation method. Specifically, techniques that compound C_i terms such as quadratic are more effective than techniques that shrink C_i terms such as logarithmic or square root
- The BAMQ is not sensitive to model run time or a_s weight until a_s is at least 0.7 or higher, depending on the S_{ij} calculation technique
- The BAMLGPD is a better model than the BAMQ for several reasons:
 - BAMLGPD improved over the baseline schedule in all instances, whereas BAMQ did not
 - BAMLGPD is a linear formulation, which allows solvers to explore more branch and bound nodes within the same run time
 - BAMLGPD is simpler formulation and does not require selecting a S_{ij} technique
 - BAMLGPD schedules perform much better when substituted into the BAMQ formulation than vice versa
- The 2BAMLGPD is limited from a practical perspective because the a_s weight equals one. However, it can solve to optimality quicker and therefore could be used as a lower bound for the BAMLGPD total SPD cost objective term

The findings of chapter four confirm most of the first research hypothesis. Mathematical OR scheduling models did improve SPD performance. However, this improvement is in terms of the mathematical formulation. In chapter six, a discrete event simulation model tests the mathematical model results in a more practical manner and completes the first hypothesis.

CHAPTER FIVE

TRAY OPTIMIZATION MODEL

This chapter covers the tray optimization model (TOM), which solves the tray optimization problem (TOP). Section one covers the background and assumptions of the problem. Section two reviews the TOM formulation. Section three details the parameter generation plan and model evaluation plan. Section four summarizes the computational results. Finally, section five discusses the results and areas for future research.

Section 1: Background and Assumptions

The Tray Optimization Problem (TOP) optimally allocates surgical instruments to trays and assigns trays to surgical procedures. The TOP has been addressed by only a handful of articles [6, 55, 61, 148, 179]. Previous articles assumed the instrument requests for surgical procedures were a hard constraint that must be met. As was mentioned in chapter 2, instrument usage rates are quite variable and preference cards are often inefficient. The proposed TOM relaxes this assumption **and is the first TOP model that incorporates expected non-usage rates for instruments**. The proposed TOM is also the first TOP model that uses goal programming.

The model assumes the expected non-usage rates are independent of patient type. In other words, the patient demographics do not affect the expected instrument usage rates for a procedure. The model also assumes expected non-usage rates are independent of the surgeon performing the procedure. The model assumes a fixed inventory of instruments. The model does not factor the total tray capacity or daily schedule of the OR suite. It also assumes there will be enough copies of the tray configurations to satisfy daily demand.

Section 2: TOM Formulation

The TOM is formulated as follows:

Parameters:

A_{ip} = Desired amount of instrument i for procedure p

W_i = weight of item i (in pounds)

W_t = weight of tray t (in pounds)

N_p = Annual frequency of procedure p

C_t = desired weight capacity of tray t (in pounds)

S_i = total inventory amount of instrument i

PC_t = penalty for tray t exceeding its desired weight capacity (per pound)

PA_{ip} = penalty for not having the desired amount of instrument i for procedure p (per item)

U_{ip} = expected non-use percentage of instrument i for procedure p (0 – 1)

MC_t = maximum factor by which tray t can exceed its desired weight capacity

MO = Maximum overage amount of instrument i for procedure p

MU = Maximum underage amount of instrument i for procedure p

Decision Variables:

Let y_{tp} =

$$\begin{cases} 1 & \text{if tray t is used for procedure p} \\ 0 & \text{otherwise} \end{cases}$$

Let b_{it} = quantity of reusable instrument i assigned to tray t

Let $s1_t^+$ = amount that tray t exceeds its desired weight limit

Let $s1_t^-$ = amount that tray t is under its desired weight limit

Let $s2_{ip}^+$ = quantity of instrument i for procedure p that is above the desired amount A_{ip}

Let $s2_{ip}^-$ = quantity of instrument i for procedure p that is below the desired amount A_{ip}

Objective:

$$\text{Min } \sum_p \sum_t \sum_i (b_{it} * y_{tp} * U_{ip} * N_p) + \sum_t (s1_t^+ * PC_t) + \sum_i \sum_p (s2_{ip}^- * PA_{ip} * N_p)$$

Subject to:

$$\sum_i (b_{it} * W_i) + W_t + s1_t^- - s1_t^+ = C_t \quad \forall t \quad (1)$$

$$\sum_t (b_{it} * y_{tp}) + s2_{ip}^- - s2_{ip}^+ = A_{ip} \quad \forall i, p \quad (2)$$

$$\sum_t b_{it} \leq S_i \quad \forall i \quad (3)$$

$$\sum_i (b_{it} * W_i) + W_t \leq MC_t * C_t \quad \forall t \quad (4)$$

$$s2_{ip}^+ \leq MO \quad \forall i, p \quad (5)$$

$$s2_{ip}^- \leq MU \quad \forall i, p \quad (6)$$

$$s1_t^-, s1_t^+ \geq 0 \quad \forall t \quad (7)$$

$$s2_{ip}^-, s2_{ip}^+ \geq 0 \quad \forall i, p \quad (8)$$

$$y_{tp} = \text{binary} \quad \forall i, p \quad (9)$$

$$b_{it}, s2_{ip}^+, s2_{ip}^- \text{ integer} \quad \forall i, t, p \quad (10)$$

$$b_{it} \geq 0 \quad \forall i, t \quad (11)$$

The objective function minimizes three terms. First, the total annual expected number of instruments that are present for a surgical case but not used. Second, the total amount the trays exceed their desired weight capacity. Third, the annual number of instruments that were requested but not assigned to surgical cases.

Constraint (1) is a goal programming constraint that links the underage and overage tray weight variables to the desired tray weight. The desired tray weight, C_t , can be thought of as the maximum allowed tray weight because the underage tray weight variable does not count towards the objective value. Constraint (2) is a goal programming constraint that links the underage and overage values of instrument preferences to the desired amount for each instrument and procedure. Constraint (3) ensures the total quantity of an instrument on all trays does not exceed the inventory amount for

that instrument. Constraint (4) places a hard constraint on the maximum amount that a tray can exceed the maximum allowable weight. Constraints (5) and (6) place hard constraints on the underage and overage amounts for instrument preferences. Constraints (7) – (11) define the categories of the decisions variables and their non-negativity.

The multiplication of binary variables results in a quadratic objective function and quadratic constraints. To ease computational complexity, the formulation is linearized in the same manner as Ahmadi and Masel [6]:

Let q_{itp} = amount of instrument i in tray t for procedure p . q_{itp} then replaces $(b_{it} * y_{tp})$ in the objective function, constraint (2), and constraint (5). Additionally, four more constraints are added:

$$\sum_i q_{itp} \leq y_{tp} * M \quad \forall t, p \quad (12)$$

$$q_{itp} \leq b_{it} \quad \forall i, t, p \quad (13)$$

$$b_{it} \leq q_{itp} - y_{tp} * M + M \quad \forall i, t, p \quad (14)$$

$$q_{itp} \geq 0 \quad \forall i, t, p \quad (15)$$

Section 3: Parameter Generation and Model Evaluation Plan

Parameters were generated based off real Bozeman Health Deaconess Hospital (BHDH) data and data from previous TOP articles. The number of procedures was 12, which was similar to [6], which had 14 procedures, and [61, 148], which both had 15 procedures. In the case of [148], the 15 procedures constituted approximately 70% of the total volume. Therefore, focusing on approximately a dozen of the most frequent cases can constitute a large proportion of overall volume while keeping the size of the procedure index low, which helps reduce the size of the problem.

In previous TOP articles, the number of trays configured is an output of the model. However, the TOM assumes the number of trays is fixed. In Ahmadi and Masel [6], the number of trays ranges

from 4-10. The number of trays for the TOM evaluation plan in this study ranged from 6-10. The instruments were generated by using the recipe lists from six of the most common BHDH tray types, which resulted in 174 unique instruments. This is comparable to the 200 unique instruments in [148]. The instruments weights were found by researching instrument vendor catalogs available on the internet. If the instrument weights could not be found, then they were assigned the same weight as a similar instrument.

The frequency of the 12 most common BHDH procedures ranged from 73 to 221. The N_p vector for the annual frequency of the procedures was generated using a uniform distribution from 73 to 221. The PA_{ip} matrix was equal to one for all values. This was done to gain a better understanding between the first and third objective terms. Recall the first objective term is the annual expected number of unused instruments. With PA_{ip} equal to 1 for all i and p , the third objective term then becomes the annual number of instruments that were requested but not on hand for the procedures. Similarly, the PC_t vector was equal to one for all values.

The A_{ip} and U_{ip} parameters were generated to create conflicts within the baseline setting. The A_{ip} parameters were generated using discrete distributions. For example, table 23 displays the A_{ip} discrete distribution for procedure 2. Of the 174 unique instruments, 65% of those instruments would not be requested for procedure 2, 12% of the 174 instruments were requested to have 1 of that instrument type on hand for procedure 2, 10% of the instruments were requested to have 2 of that instrument type on hand for procedure 2, and so on. The total number of instruments requested ranged from 0 to 8, which created natural conflict with the total inventory (S_i) value for each instrument, which ranged from 10 to 15. For each procedure, the U_{ip} parameter followed a normal distribution summarized by table 24.

The parameter generation resulted in baseline values summarized by table 25. Per Bozeman Health Deaconess Hospital (BHDH), the total allowable weight for each tray (C_t) is 30 pounds. A 10% buffer was given to the maximum allowable tray weight (MC_t). Altogether, the parameters yield

a total annual expected number of unused instruments of 70,748 and an expected annual instrument utilization rate of 70.7%. The TOM evaluation plan systematically altered the number of trays available, model run time, and the MU and ML values.

Table 23: A_{ip} Parameter Summary for Procedure 2

Number of instrument i requested	Probability
0	0.65
1	0.12
2	0.1
3	0.08
4	0.04
5	0.01
6	0
7	0
8	0

Table 24: U_{ip} Parameter Summary

Procedure	Mean	Standard Deviation
1	0.35	0.25
2	0.35	0.15
3	0.35	0.1
4	0.3	0.25
5	0.3	0.15
6	0.3	0.1
7	0.25	0.25
8	0.25	0.15
9	0.25	0.1
10	0.2	0.25
11	0.2	0.15
12	0.2	0.1

Figure 16 displays the TOM evaluation plan. The number of trays ranged from 6-10. Model run times were one hour, nine hours, and one day. Although the TOP problem is computationally complex and the long-term time horizon allows for run times exceeding one day [148], one and nine hour run times were conducted to gain an idea of how the model's results improve as run time

increases. The big M parameter was set to 10,000. The MU and ML levels ranged from two to four.

A MU and ML value of one is too hard of a constraint, while values over four are too soft given the A_{ip} values.

Table 25: Baseline Metrics

	Procedure											
	1	2	3	4	5	6	7	8	9	10	11	12
# Unique Instruments requested	52	61	49	51	55	52	77	48	36	61	46	63
# Instruments Requested	142	167	116	108	162	81	172	129	93	149	104	137
Expected # Instruments Not Used	57.72	65.83	40.17	31.90	47.03	26.41	48.90	32.89	23.67	32.63	22.64	28.33
Expected Instrument Utilization	0.59	0.61	0.65	0.70	0.71	0.67	0.72	0.75	0.75	0.78	0.78	0.79
Expected Annual Unused Instr.	9177	11783	4299	6539	6490	4067	6894	3848	3101	6494	1924	6119
Total Weight Instruments Requested	50.81	77.42	44.54	39.83	58.96	33.92	78.175	55.55	42.19	58.86	52.51	61.69
N_p	159	179	107	205	138	154	141	117	131	199	85	216

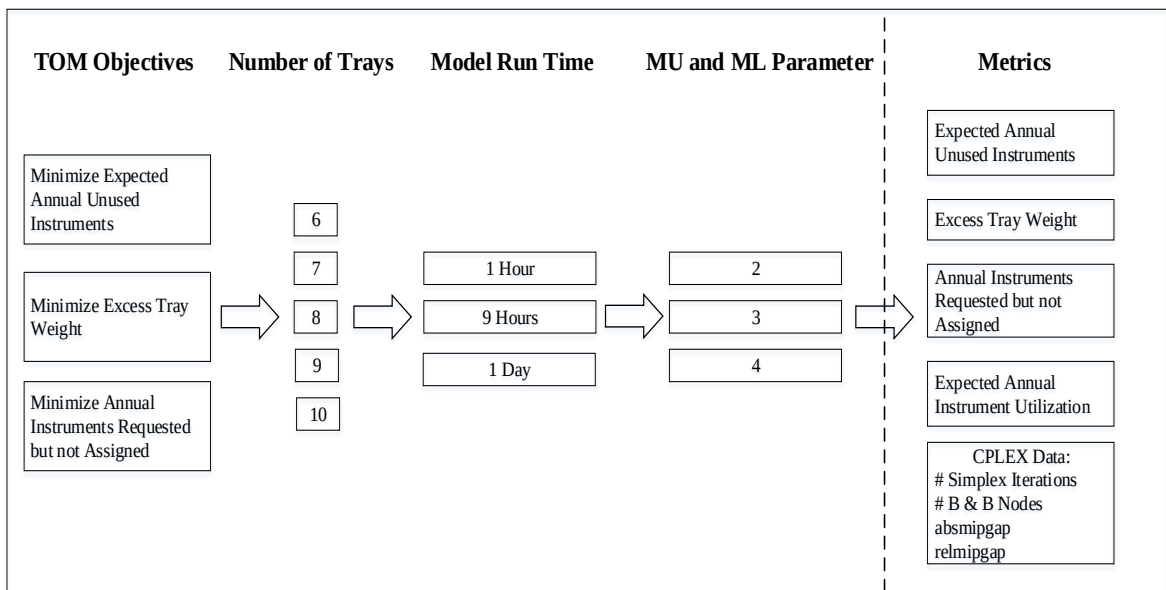


Figure 16: TOM Evaluation Plan

Section 4: Computational Results

The model was run using AMPL version 3.1 with CPLEX version 12.8 on a 64 bit 2.9GHz Intel Core Processor with 16.0 GB RAM using Microsoft Windows 10. The code used for the AMPL formulation is shown in Appendix B. Table 26 displays the results summary. Runs with dashes denoted CPLEX could not find a feasible solution.

The three objective terms and CPLEX information are shown for each run. Additionally, the annual expected instrument utilization is shown. Recall that the baseline annual number of unused instruments was 70,748 and the annual expected instrument utilization was 0.707. The model produced configurations that resulted in a lower expected annual number of unused instruments in 10 of the 36 runs, which are denoted with an asterisk and highlighted in gray in table 26. This is a promising result considering there were more procedures than trays. The model often allocated the same tray to multiple procedures, which means there are inherently going to be several instances in which instruments are on a tray but will never be used for certain procedures that involve the tray. Furthermore, the annual expected instrument utilization improved in every run, which is quite encouraging.

Practical implications of the TOM could include insight on the made to stock (MTS) versus made to order (MTO) dynamic facing OR managers. MTO preference cards for every surgeon/case combination would result in high instrument utilization but significant time and coordination on OR staff. MTS preference cards would result in lower instrument utilization but less time and coordination. The best solution may lie somewhere in between a total MTS and total MTO configuration. The TOM results could be used as to establish a starting point along the spectrum for OR managers as they decide how much and when to customize preference cards.

Table 26: TOM Computational Results

Run Time (hours)	T	MU	ML	Absmipgap	Relmipgap	MIP Simplex Iterations	Branch and Bound Nodes	1 st Obj Term: Annual # of Unused Instruments	2 nd Obj Term: Total Tray Overage Weight	3 rd Obj Term: Annual # of Instruments Requested not Assigned	Objective Function Value	Expected Annual Instrument Utilization
1	6	2	2	--	--	15284909	112051	--	--	--	--	--
9	6	2	2	--	--	172194255	683884	--	--	--	--	--
24	6	2	2	--	--	455885183	1486816	--	--	--	--	--
1	6	3	3	63541	0.394	5461337	19651	80628	17.88	80646	161292	0.737
9	6	3	3	62722	0.390	44125677	57196	79595	17.78	81397	161010	0.734
24	6	3	3	59900	0.377	108951061	107151	70510*	17.85	88364	158891	0.748
1	6	4	4	58970	0.379	5803954	19662	77796	17.8	77635	155448	0.744
9	6	4	4	56251	0.367	43747554	52234	67620*	17.9	85626	153264	0.757
24	6	4	4	54909	0.358	113947897	115700	67620*	17.9	85626	153264	0.757
1	7	2	2	--	--	3903783	64972	--	--	--	--	--
9	7	2	2	79797	0.465	97060291	386243	68117*	20.95	103490	171628	0.728
24	7	2	2	77504	0.458	320250104	1032251	70481*	20.91	98837	169339	0.729
1	7	3	3	63208	0.416	3172129	15302	84309	20.54	67713	152042	0.741
9	7	3	3	61692	0.410	26824189	37233	72502	20.85	78004	150527	0.747
24	7	3	3	61448	0.409	94751421	97804	78567	20.91	71699	150287	0.743
1	7	4	4	58917	0.402	3008472	13536	78843	20.49	67831	146695	0.750
9	7	4	4	56203	0.390	27862904	36782	67638*	20.97	76322	143981	0.753
24	7	4	4	58090	0.398	89487281	88911	73545	20.77	72354	145920	0.758
1	8	2	2	86762	0.510	2087249	11297	88675	23.58	81453	170152	0.731
9	8	2	2	86534	0.509	14212444	26028	88945	23.44	80955	169924	0.729
24	8	2	2	86525	0.509	37918007	43962	89290	23.49	80601	169915	0.729
1	8	3	3	65440	0.444	3209819	12167	83679	23.7	63692	147395	0.743
9	8	3	3	61423	0.428	20839755	38619	75618	23.64	67735	143377	0.746
24	8	3	3	58464	0.416	44672705	35980	80908	23.82	59486	140418	0.748
1	8	4	4	61962	0.433	3734150	15396	78412	23.66	64763	143198	0.753
9	8	4	4	55948	0.408	24383934	35319	70205*	23.81	66955	137184	0.758
24	8	4	4	55791	0.407	63699573	57788	64555*	23.8	72449	137028	0.753
1	9	2	2	79493	0.507	2752922	8016	80207	26.64	76684	156918	0.723
9	9	2	2	71826	0.481	21419421	29743	75647	25.35	73577	149249	0.739
24	9	2	2	69725	0.474	63303739	57277	84971	26.54	62152	147149	0.737
1	9	3	3	62962	0.451	2528999	10516	72077	26.61	67624	139728	0.742
9	9	3	3	59428	0.436	12633638	15372	73419	26.85	62749	136194	0.744
24	9	3	3	56639	0.425	55043143	69908	77801	26.82	55577	133405	0.751
1	9	4	4	58378	0.433	2432221	10194	67045*	26.82	67671	134742	0.754
9	9	4	4	55857	0.422	16142696	22070	70227*	26.8	61967	132221	0.749
24	9	4	4	52824	0.409	61158738	67769	74462	26.55	54700	129189	0.752

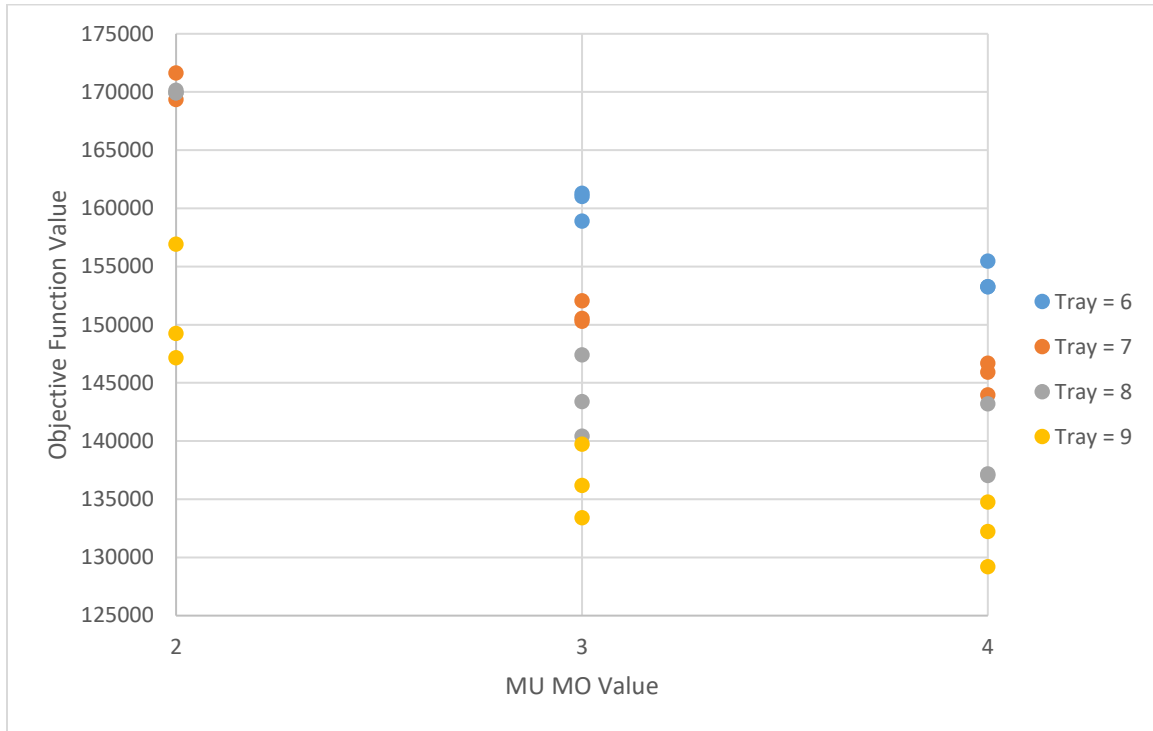


Figure 17: Objective Value by MU MO Values

Figure 18 displays the relationship between the objective value and expected annual instrument utilization rate. Not surprisingly, as the objective value improves (decreases), the utilization rate increases. A similar intuitive trend emerges between the first objective term and the tray and MU/MO values. As figure 19 shows, as the hard constraints MU and MO become more relaxed and more trays are available, the expected annual number of unused instruments decreases. For simplicity, figure 19 only shows the values for the 24 hour run times.

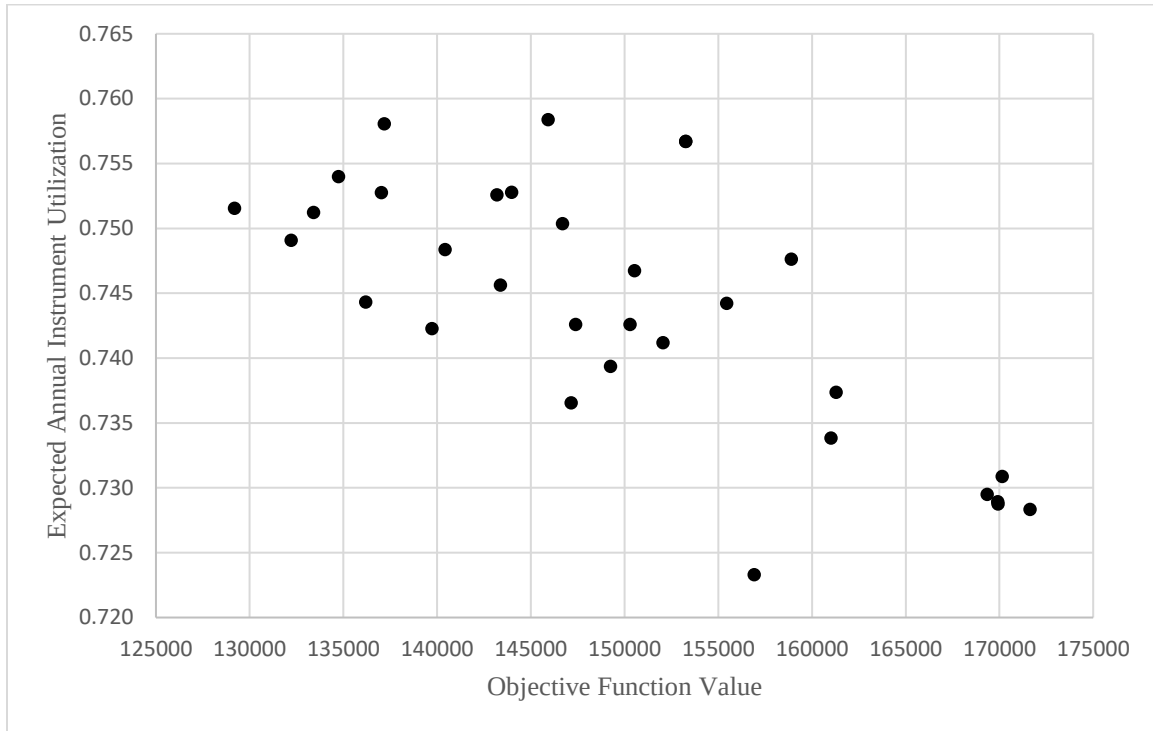


Figure 18: Objective Value vs. Annual Expected Instrument Utilization

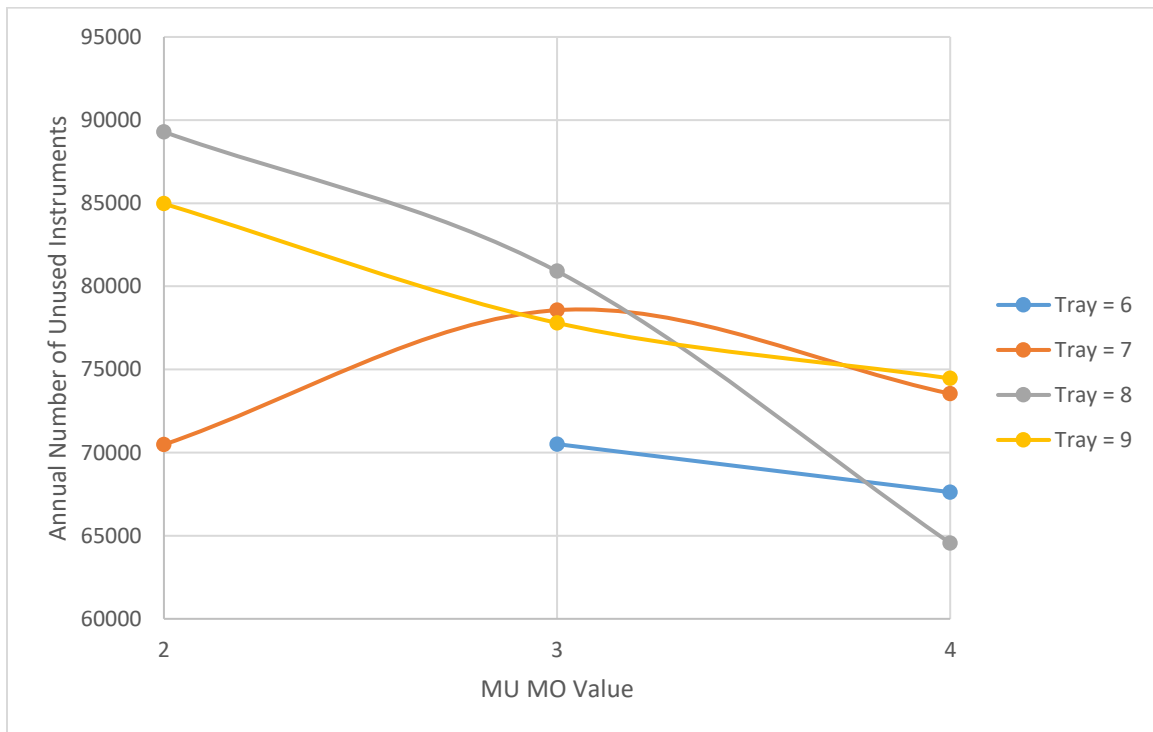


Figure 19: Annual Number of Unused Instruments by Tray and MU MO Value

Section 5: Discussion/Areas for Future Research

The initial TOM results are encouraging. The model improved expected instrument utilization rates in every instance. The model even decreased the number of unused instruments in several runs even though it faced a considerable disadvantage from the “baseline” metric which did not face limited tray capacity. Altering the three parameters of run time, number of trays, and MU MO values yield intuitive results.

The TOM does have limitations. As with similar TOP articles, the model quickly reaches a certain size (number of procedures, trays, and instruments) that is no longer manageable. The TOM assumes there are enough trays to make copies of all the different tray configurations for the day, however, this may not always be the case. The assumption of patient demographics and surgeon not affecting instrument usage rates may not be valid.

The limitations impact how broadly the results can be interpreted. While the model parameters were generated based off historical data and previous TOP research articles, it will not be known for certain if the TOM can achieve similar improvements in an applied setting. Similarly, several of the model assumptions could be relaxed for future research (which will be discussed in the next paragraph). However, until this research is carried out it is difficult to predict the model’s effectiveness. This does not mean that the results from this study are not worthwhile. Rather, it speaks to the newness of the TOP as a research problem. As researchers systematically build upon the TOP, the number of assumptions and limitations that affect how broadly the results can be interpreted should hopefully decrease.

Several areas for future research exist for the proposed TOM. Now that the model has shown promising results based on generated data, future research lies in applying the model to a specific OR suite setting. This would involve a longitudinal study collecting instrument usage rates for the U_{ip} parameter preferences along with the A_{ip} values over a period of time. The PA_{ip} and PC_t parameters

could be further refined, though setting them equal to one for all cases as this research study did provided adequate results. Conducting the instrument usage rate data collection would also demonstrate whether the assumption of surgeon and patient independence for the U_{ip} parameter is valid. The fixed inventory assumption could be relaxed. A heuristic that reduces model run time could be developed and compared to the initial TOM results. Finally, the daily schedule and total tray capacity of the OR suite could be a factor in to a more comprehensive TOM.

The second research hypothesis of this study was that a goal programming model can improve preference cards and SPD throughput. This chapter presented a tray optimization model (TOM) that assigned instruments to trays and trays to surgical case preference cards based upon current inventory, surgeon preferences, and total allowable tray weight. This is the first TOP model that 1) using goal programming and 2) relaxes the assumption that all instrument requests must be met. A model evaluation plan was conducted to examine how altering model run time, number of trays, and maximum overage/underage levels impacted solution quality. Several key takeaways emerged:

- The TOM improved expected instrument utilization rates in every instance
- Though TOM was disadvantaged compared to the baseline metric in terms of tray capacity, it still decreased the expected number of unused instrument in several instances
- TOM is sensitive to run time. Longer run time improves solution quality.
- As the maximum overage/underage amounts are relaxed and more trays are available, expected annual number of unused instruments decreases
- From a practical perspective, the TOM could be used by OR managers as a starting point to decide when and how much customization (MTS versus MTO) will occur in their preference cards

The findings of chapter five confirm most of the second research hypothesis. A goal programming model did improve preference cards. However, this improvement is in terms of the expected instrument utilization rates within the OR. In chapter six, a discrete event simulation model tested the TOM results to determine if the SPD performance improved.

CHAPTER SIX

SIMULATION MODEL

This chapter examines the impact on the SPD from the schedules generated in chapters 4 and 5. A comprehensive simulation model was developed to test these schedules. This chapter is divided into five sections. Section one outlines the data collection that took place to build the simulation model. Section two describes the sterilization process within the SPD and the conceptual model. Section three covers simulation model verification and validation process. Section four details the simulation results of the block assignment model schedules from chapter four. Section five covers the simulation results from the tray optimization model from chapter five.

Section 1: Data Collection

The Bozeman Health Deaconess Hospital (BHDH) SPD was observed for approximately eight weeks. The observation and input from SPD staff allowed the author to gain a thorough understanding of the SPD work flow, which is described in the next section. During the observation, the author recorded the times to rinse and assemble surgical cases. A wide variation existed in these processing times. For example, a spine case or robotic knee case could take over two hours to rinse and assemble while a simple tonsillectomy case could take under 20 minutes. The other stages in the sterilization process, such as the dirty side washing machine and clean side autoclave machine, are identical regardless of case type. However, larger cases consume more machine capacity than smaller cases.

After the rinse and assembly processing times were collected, probability distributions were calculated by case type. The Kolmogorov-Smirnov test [23] was used for goodness of fit, with a minimum p-value of 0.05 required to use the distribution. If a case occurred only once or twice during the data collection period, then a deterministic duration was used. For the rinse processing

times, distributions were calculated by case type. For example, a total knee case that consisted of several trays may take 35 minutes. For the assembly process, however, cases often are not assembled at once. For example, the same total knee case may be composed of one Ortho Major tray, one Arthrex vendor tray, 3 wraps, and 6 peel packs. This required the assembly process to be captured at the subcomponent level. A total assembly time distribution was then calculated as the sum of the individual subcomponent assembly distributions.

In addition to direct observation, this research study utilized three BHDH datasets. The first dataset contained records for every OR surgery performed from 2011 to 2014, totaling 18,071 unique surgeries and 567 different surgical procedures. This dataset was used to calculate the probability distributions for the surgical case durations for [134] and the same information was used for the majority of the case types in the new simulation model. This dataset was also used to calculate the historical non-elective case arrival rate. The five most common types of non-elective cases and their approximate frequencies were used for the simulation model.

A second BHDH dataset containing every OR surgery from January 2018 to June 2018 was also used for the research study. This dataset, which contained approximately 6,268 unique surgeries, was used to generate the baseline schedule. The baseline schedule was then used to generate the expected total SPD processing time by surgical group, C_i , for the block assignment model in chapter four. As will be discussed later in this chapter, the baseline schedule was also simulated and the results were compared with the simulation results of the schedules generated by the models in chapter four. Additionally, there were approximately 21 surgical case types that were not in the previous data set that occurred in the generated baseline schedule. Probability distributions for these surgical case times were calculated using the same methodology as the SPD rinse and assembly processing times.

The final dataset this research study utilized was a BHDH SPD productivity report. During the direct observation period, the non-OR case arrival rate to the SPD was calculated to follow an exponential distribution. However, SPD case volume was lower than average during the observation

period. Therefore, the productivity dataset was used to calculate the mean number of non-OR case arrivals to the SPD for a typical weekday.

Section 2: Sterilization Process and Conceptual Model

The sterilization process requires several steps. Instruments arrive to the SPD's dirty room through two different means depending on their origin. OR instruments arrive via the dirty elevator from the OR suite that is one floor above the SPD. Non-OR instruments are dropped off by non-OR department staff at the door that leads into the dirty room from the external hallway. Instruments are first manually rinsed by a SPD staff. Then, they are placed in one of three washing machines. When the washing machine cycle is complete, SPD staff unload the instruments through the back side of the washing machine into the clean side of the SPD. After drying, SPD staff assemble the instruments into a tray, wrap, or peel pack. Next, the assembled item is put into an autoclave machine for sterilization. Finally, the item must cool down to room temperature after sterilization and is then sent back to the OR via the clean elevator or placed in a pick-up area where non-OR department staff retrieve the item.

The simulation model began with the existing simulation model from [134]. Figure 20 displays the conceptual model from this article. Entities (surgical cases) are created through an Excel file that depicts the OR schedule. Each entity seizes its assigned OR at its scheduled case time if the OR is currently available. The OR is delayed by the surgical case's probability distribution, then a general turnover distribution, and then released. The metrics of interest in [134] were number and magnitude of tardy surgeries and the simulation recorded this information after each case was complete.

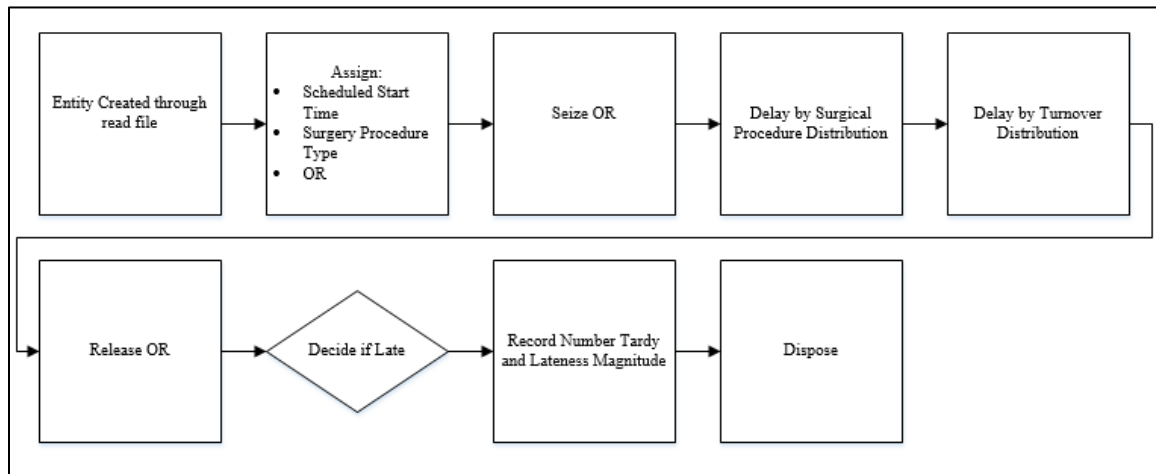


Figure 20: Original OR Conceptual Model

This research study then developed the simulation logic for the SPD after a surgical case ends. Appendix C contains screenshots of the simulation model in Arena. Figure 21 displays the comprehensive OR and SPD simulation model. The primary addition to the original simulation model is the right half of figure 21, which represents the SPD. The SPD portion of the simulation model follows from the previously described sterilization process.

Additions were made to the OR suite portion of the simulation model. First, the new excel schedule file contains washing and autoclave machine sizes for surgical cases. This information plays a role in the batching logic for the washing and autoclave machines. Second, the model now contains the dedicated labor and delivery room, which the original model did not. Finally, non-elective cases arrive as separate entities. In the original model, the non-elective cases were scheduled according to when they had arrived and in what OR they were assigned to for the given week. In the new model, non-elective cases arrive according to their historical arrival rate. The non-elective cases have priority over all elective cases, but do not interrupt any elective cases that have already started (non-preemptive priority). In other words, a non-elective cases moves to the front of the OR queue and seizes the first OR that becomes available. Non-elective labor and delivery cases were only allowed to go to the designated labor and delivery room.

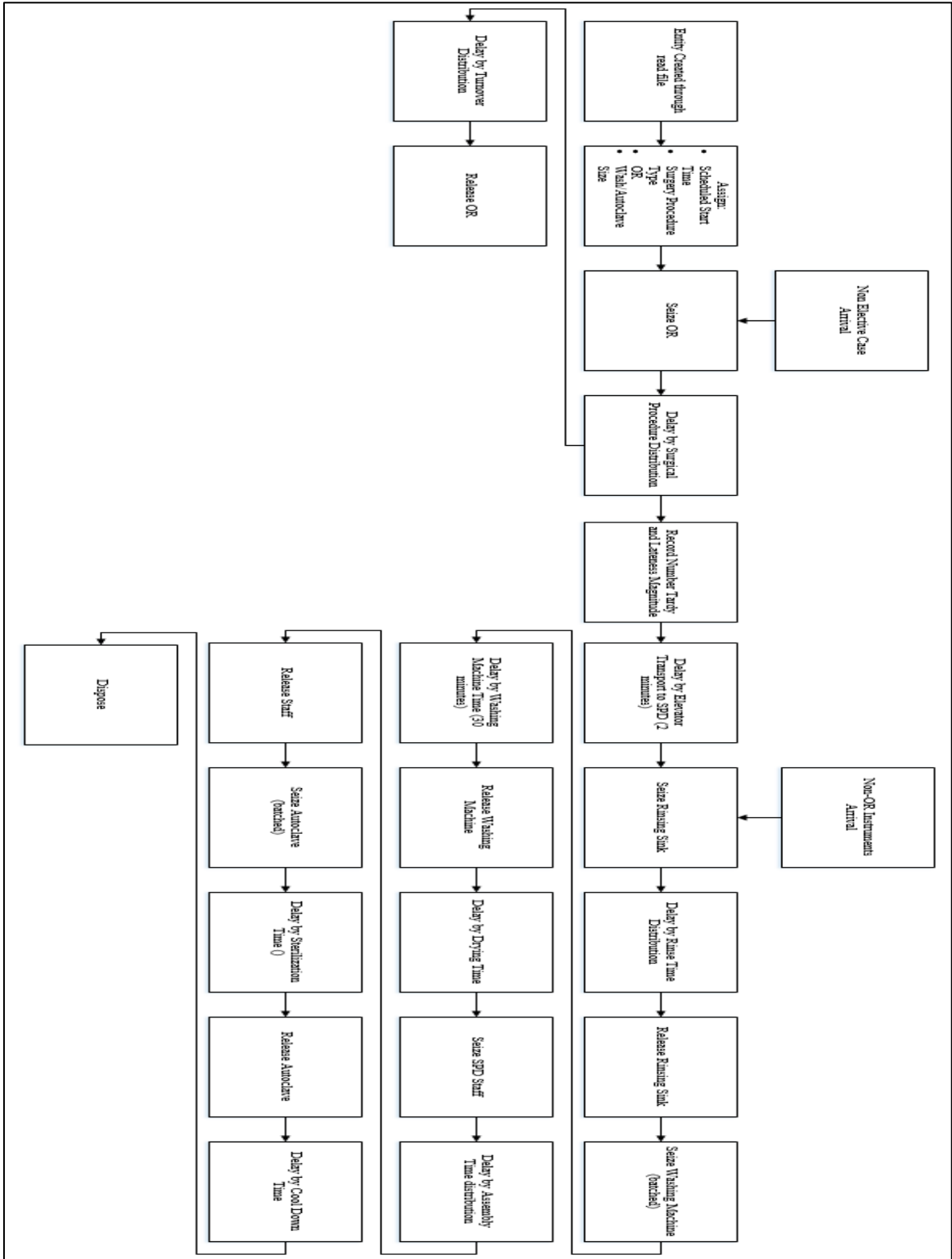


Figure 21: Comprehensive OR SPD Simulation Model

The simulation logic for the SPD follows the sterilization process. Two SPD staff are available to manually rinse cases at the two sinks in the dirty room. The model assumes no staff breaks during the day and the staff have similar proficiency in rinsing cases. During the observation period, SPD staff swapped out with one another throughout the day, resulting in a continuously manned rinsing station.

Three washing machines process the rinsed cases. The simulation model utilized the separate and adjustable batch functions in Arena to represent how cases fit into washing machines. Certain surgical cases, such as spine procedures, have much larger preference cards and require more space in washing machines than smaller cases such as tonsillectomies. After the rinsing station, cases are cloned according to their case size. An adjustable batch module then batches the cases according to the washing machine capacity. After the batched groups finish drying, they are re-batched back into their original surgical cases.

After drying, the cases seize one of three SPD staff for assembly into the trays, wraps, and peel packs that compose the case. The model assumes the SPD staff have similar proficiency in assembling cases. The model also assumes three continues staff are available for assembly throughout the day for the same reason as the manual rinsing station. The autoclave sterilization process logic follows the washing machine logic. Cases are cloned according to how much space they consume in the autoclave. An adjustable batch module then batches the cases for the autoclave machine. After sterilization and cool down, the group cases are separated and re-batched back into their original surgical cases.

In addition to the original OR-related metrics, the new simulation model records several SPD metrics of interest. For the dirty side of the SPD, the model records the number of cases that wait to be rinsed, the number of cases that do not wait to be rinsed, the rinse wait time for cases that wait to be rinsed, and the total rinse station time (wait time plus rinse processing time). For the clean side of the SPD, the model records the number of cases that wait to be assembled, the number of cases that

do not wait to be assembled, the assembly wait time for cases that wait to be assembled, and the total case assembly station time (wait time plus assembly processing time). The model also records the total case turnaround time, which starts when a case arrives in the dirty room and ends when the case has finished cooling down after the autoclave. Table 27 summarizes the simulation model metrics of interest. Each of the nine metrics is also recorded by what day the case occurs.

Table 27: Simulation Model Metrics of Interest

Simulation Model Metrics of Interest	
1	Average Rinse Station Time
2	Average Assembly Station Time
3	Average Case Turnaround Time
4	Average Rinse Wait Time for those who Wait
5	Average Assembly Wait Time for those who Wait
6	Average Number who Wait for Assembly
7	Average Number who Wait for Rinse
8	Average Number who do not Wait for Assembly
9	Average Number who do not Wait for Rinse
10 – 54	The above 9 metrics for each weekday

Section 3: Model Verification and Validation

The simulation model was then verified. The verification plan systematically tested the different elements of the new simulation model. Table 28 summarizes the first 19 verification tests, which primarily address entity flow, batching/separate functions, and metric calculations. For these tests, the surgery procedure time, turnover time, SPD rinse time, and SPD assembly time were fixed to 10 minutes. Arrival time refers to the number of minutes into the simulation time. For example, 0 corresponds to 7:30 AM Monday and 1440 to 7:30 AM Tuesday morning. The elevator to the SPD and post washing machine dry time were 5 minutes, and the washing machine, autoclave, and post autoclave cool down times were 30 minutes.

Table 28: Verification Plan Tests 1-19

Test #	Test Description	Entities in System	Autoclave Size	Wash Size	Arrival Time	Expected Result
1	Elective case flow, testing batching/separate functions, day metric calcs	1, OR 1	48	36	0 (Monday)	Avg Case Turnaround Time of 175
2		1, OR 2	48	36	1440 (Tuesday)	Avg Case Turnaround Time of 175
3		1, OR 3	48	36	2880 (Wednesday)	Avg Case Turnaround Time of 175
4		1, OR 4	48	36	4320 (Thursday)	Avg Case Turnaround Time of 175
5		1, OR 5	48	36	5760 (Friday)	Avg Case Turnaround Time of 175
6		1, OR 6	48	36	0	Avg Case Turnaround Time of 175
7		1, OR 7	48	36	0	Avg Case Turnaround Time of 175
8		1, OR P2	48	36	0	Avg Case Turnaround Time of 175
9	Adjustable batch function	2, OR 1	6	3	0,120	Avg Case Turnaround Time of 155
10		2, OR 2	6	3	0,120	Avg Case Turnaround Time of 155
11		2, OR 3	6	3	0,120	Avg Case Turnaround Time of 155
12		2, OR 4	6	3	0,120	Avg Case Turnaround Time of 155
13		2, OR 5	6	3	0,120	Avg Case Turnaround Time of 155
14		2, OR 6	6	3	0,120	Avg Case Turnaround Time of 155
15		2, OR 7	6	3	0,120	Avg Case Turnaround Time of 155
16		2, OR P2	6	3	0,120	Avg Case Turnaround Time of 155
17	Non Elective OR 1 Flow Seize OR Priority	2 OR 1, 1 NE OR 1	12	18	0, 5, NE-6	The non elective OR 1 case should jump in front of the 2nd OR 1 elective case and be processed first, once the turnover in OR 1 is complete.
18	Non Elective OR Flow Seize OR priority	2 each OR 2-P2, 8 NE General	12	18	0,5,NE-6	The non elective OR cases should jump in front of the 2nd elective cases and be processed first.
19	Combined Non Elective Case Flow	2 each OR 1-P2, 8 NE General, 2 NE OR 1			0,5,NE-6	The non elective OR cases should jump in front of the 2nd elective cases and be processed first. The NE OR 1 cases should jump in front of the OR case and be processed first. The NE OR 1 case should go to OR 1 and the general NE cases should go to any OR except OR 1

The metric used to verified tests 1-16 was average case turnaround time. Tests 17-19 were run by time step with animation to verify the non-elective cases successfully moved to the front of their respective OR queue. Test 1-19 were successfully verified.

Table 29 summarizes tests 20-24. These tests involved multiple entities going through the SPD at once and checks that the wait time metrics are successfully calculated. Tests 20-24 used the same fixed parameters as tests 1-19 except the drying time was 25 minutes for tests 20-23 and the washing machine time was 10 minutes for test 20. These tests were run by time step with animation to verify correct flow. All tests were successfully verified.

Table 29: Verification Tests 20-24

Test #	Test Description	Entities in System	Autoclave Size	Wash Size	Arrival Time	Expected Result
20	SPD Rinse, Assemble Calcs	1 x OR 1-4	8	2	0,0,0,5	Change assembly staff to 2 instead of 4. Checks SPD Wait and avg rinse, assembly metrics. 1 waits for rinse for 5 min, 1 waits for rinse for 10 min, 1 wait for assembly at 10 minutes. Avg Rinse time for those who wait is 7.5, avg assemble wait time for those who wait is 10
21	SPD Rinse, Assemble Calcs multiple days	1 x OR 1-4	8	2	0,0,0,4 1440 x 3 and 1445	Change assembly staff to 2 instead of 4. Checks SPD Wait and avg rinse, assembly metrics. For Monday 1 waits for rinse for 6 min, 1 waits for rinse for 10 min, 1 wait for assembly at 10 minutes. AVG Rinse time for those who wait is 8, avg assemble wait time for those who wait is 10. For Tuesday, avg rinse wait time for those who wait is 7.5, avg assemble wait time for those who wait is 10. Overall rinse wait time for those who wait is 7.75, assembly 10. Also run this test for Wed and Thurs, Thurs and Fri to confirm metrics work for each day.
22	Re-batching functions	1 x OR 1-3	4	2	0	The 3 cases should successfully re-batch back to their original entity after washing machine and autoclave. Turnaround time of 145
23	SPD Non OR Arrival Flow	1 x SPD non OR	48	36	0	Average turnaround time of 195. Also checks the day calc functions.
24	SPD Non OR Arrival Re-batching functions	3 x SPD non OR	4	2	0	The 3 cases should successfully re-batch back to their original entity after washing machine and autoclave. Turnaround time of 145

Recall the original OR simulation model was validated in [134]. The SPD portion of the simulation model was validated based on discussion with SPD staff and two months of in-depth observations. The SPD portion of the new comprehensive simulation model was not validated based on observed metrics for several reasons. SPD staff do not assemble the cases using any systemic structure or sequencing rule that can be modeled. SPD staff cannot identify the original case for an item they are currently processing. In general, SPD staff randomly choose an item from the assembly queue to assemble based upon their personal preference and there is a wide range in rinsing and assembling proficiency based on how experienced the particular staff member is. This randomness would be incredibly difficult to model and validated based on observed data. Furthermore, subcomponent items do not maintain case integrity after the rinsing station, which makes tracking the progress of a case virtually impossible. There is no bar code system within the SPD that tracks the status of items.

The previous SPD simulation articles follow a similar pattern for model validation. Of the two previous research articles that built a SPD simulation model, only Di Mascolo and Gouin [51] were able to “validate” the model based on observed metrics. However, the two metrics Di Mascolo and Gouin [51] used for model validation were the mean number of washing and autoclave cycles. These two metrics only convey how many items are processed by the SPD. They do not actually relate to the stochastic nature of the sterilization process like metrics such as case turnaround time does. The one SPD simulation research article that did use case turnaround time, Lin et al. [108], similarly relied on extensive observations and discussions with SPD staff for model validation. Recall the purpose of the simulation model is to test the results of the research models, compare them to a baseline, and determine if SPD performance improved. The schedules generated by the research models and the current baseline schedule are both simulated under identical conditions, which allows for a fair comparison in accordance with the research objectives.

The baseline schedule from the January – June 2018 data set and the block assignment model schedules from chapter four were run in Arena version 15.1 on Windows 10. To test the TOM results, the baseline schedule was simulated with decreased SPD rinsing and assembly processing times to mimic the effect of preference cards with fewer instruments. Figure 22 summarizes the simulation testing methodology. The only change between the baseline schedule and chapter four schedules was which surgical groups had which block times in the different ORs. The surgical schedule (start time and case type) of each surgical group remained the same.

The model was run such that the number of replications yielded a half width percentage for the average assembly wait time for those who wait that was within 5% of the mean. Using a significance level of 0.05, this resulted in 200 replications per run. Randomly sampling 9 of the simulation run times yielded an average run time of 178.22 seconds with a standard deviation of 9.93 seconds. The simulation model ran continuously from Monday at 7:30 AM to Friday at 9:30 PM, however, normal operating hours for the OR are 7:30 AM – 5:30 PM. Therefore, any non-elective or non-OR SPD arrivals outside of the normal workday were disposed prior to entering the SPD.

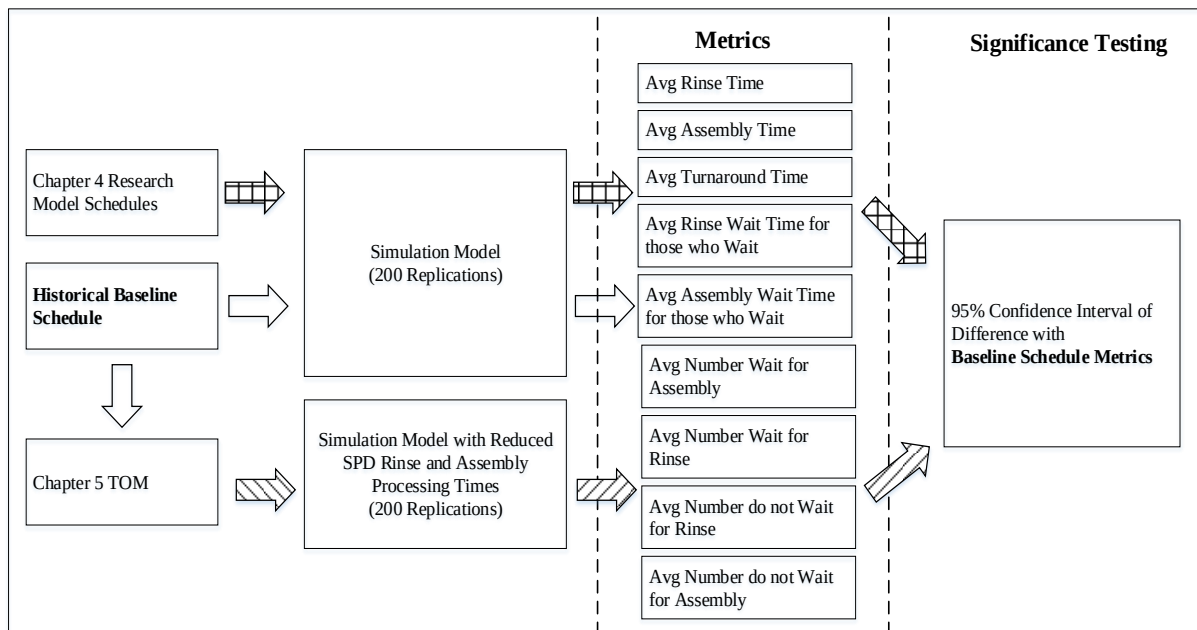


Figure 22: Simulation Testing Methodology

Section 4: Block Assignment Model Schedule Results

Tables 30-34 summarize the BAMQ, BAMLGPD, and 2BAMLGPD simulation results. The baseline schedule is shown in the first row for comparison. All processing times are in minutes. The serial number column refers to the same serial number in chapter 4. For each schedule and metric, a 95% confidence interval of the difference between the metric and the baseline schedule metric was calculated to determine if the result was statistically significant. The confidence interval assumed unequal variances between the two schedules and used the student's t distribution. In each table, metrics that are a statistically significant improvement are denoted by an asterisk and highlighted in gray.

Tables 30-34 show instances of significant metric improvements in all models. No instances occurred in which a model schedule had a metric that was significantly worse than the baseline schedule. However, certain models appear to have more improvements than others. Table 35 displays the number of statistically significant metric improvements by model. Recall for each model- a_s weight combination, there were 4 run times resulting in 36 potential instances for improvement. With the 6 different a_s weights, there were 216 potential instances for metric improvement for each model. The “% Rate” column gives the percentage for the number of metric improvements out of 216 for each model. The 2BAMLGPD only occurs for an a_s value of one and had three run times. If the model would have been run for nine hours, then it would have produced the same schedule as the one hour run because it reached optimality in just under one hour. Therefore, the number reported in table 35 for 2BAMLGPD assumes four run times for an equivalent comparison to the other models.

Table 30: BAMQ Quadratic Simulation Results (all times are in minutes)

Run Time (Seconds)	a _s Weight	Serial Number	Avg. Rinse Station Time	Avg. Assembly Station Time	Avg. Turnaround Time	Avg. Rinse Wait Time for those who Wait	Avg. Assembly Wait Time for those who Wait	Avg. Number Wait for Assembly	Avg. Number Wait for Rinse	Avg. Number do not Wait for Assembly	Avg. Number do not Wait for Rinse
--	--	Baseline	25.28	50.90	202.25	17.22	30.87	105.34	85.66	126.09	106.38
60	0.5	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
600	0.5	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
3600	0.5	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
32400	0.5	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
60	0.6	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
600	0.6	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
3600	0.6	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
32400	0.6	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
60	0.7	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
600	0.7	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
3600	0.7	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
32400	0.7	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
60	0.8	3	24.17*	50.05	200.27	15.25*	29.87	105.02	83.60	127.79	106.22
600	0.8	3	24.17*	50.05	200.27	15.25*	29.87	105.02	83.60	127.79	106.22
3600	0.8	2	24.28*	50.11	200.63	15.98	30.78	102.05	80.91	130.87*	109.64*
32400	0.8	2	24.28*	50.11	200.63	15.98	30.78	102.05	80.91	130.87*	109.64*
60	0.9	6	24.30*	48.86*	199.61*	16.70	29.51	96.37*	77.29*	134.46*	114.97*
600	0.9	6	24.30*	48.86*	199.61*	16.70	29.51	96.37*	77.29*	134.46*	114.97*
3600	0.9	7	23.84*	49.12*	199.22*	15.36*	29.01	99.66*	78.73*	133.05*	112.04*
32400	0.9	7	23.84*	49.12*	199.22*	15.36*	29.01	99.66*	78.73*	133.05*	112.04*
60	1	6	24.30*	48.86*	199.61*	16.70	29.51	96.37*	77.29*	134.46*	114.97*
600	1	20	23.40*	49.30	198.94*	14.40*	29.19	101.04	78.11*	134.36*	111.31*
3600	1	11	24.18*	49.62	200.04*	16.00	29.99	101.56	80.01*	132.31*	110.62*
32400	1	17	24.59	50.98	201.82	17.70	34.07	100.46*	80.11*	129.67*	108.29

Table 31: BAMQ Linear Square Simulation Results (all times are in minutes)

Run Time (Seconds)	a_s Weight	Serial Number	Avg. Rinse Station Time	Avg. Assembly Station Time	Avg. Turnaround Time	Avg. Rinse Wait Time for those who Wait	Avg. Assembly Wait Time for those who Wait	Avg. Number Wait for Assembly	Avg. Number Wait for Rinse	Avg. Number do not Wait for Assembly	Avg. Number do not Wait for Rinse
--	0.5	Baseline	25.28	50.90	202.25	17.22	30.87	105.34	85.66	126.09	106.38
60	0.5	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
600	0.5	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
3600	0.5	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
32400	0.5	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
60	0.6	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
600	0.6	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
3600	0.6	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
32400	0.6	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
60	0.7	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
600	0.7	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
3600	0.7	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
32400	0.7	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
60	0.8	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
600	0.8	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
3600	0.8	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
32400	0.8	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
60	0.9	9	24.32*	49.66	200.18	15.75*	29.73	101.10	80.86*	130.82*	110.53*
600	0.9	9	24.32*	49.66	200.18	15.75*	29.73	101.10	80.86*	130.82*	110.53*
3600	0.9	9	24.32*	49.66	200.18	15.75*	29.73	101.10	80.86*	130.82*	110.53*
32400	0.9	9	24.32*	49.66	200.18	15.75*	29.73	101.10	80.86*	130.82*	110.53*
60	1	19	25.45	51.32	203.01	18.02	32.54	103.88	83.80	128.42	108.23
600	1	12	24.30*	49.47	200.09*	16.41	30.52	97.89*	78.48*	132.71*	113.17*
3600	1	16	23.99*	49.75	200.05*	15.26*	29.92	100.50*	79.83*	131.97*	110.95*
32400	1	16	23.99*	49.75	200.05*	15.26*	29.92	100.50*	79.83*	131.97*	110.95*

Table 32: BAMQ Log Simulation Results (all times are in minutes)

Run Time (Seconds)	a _s Weight	Serial Number	Avg. Rinse Station Time	Avg. Assembly Station Time	Avg. Turnaround Time	Avg. Rinse Wait Time for those who Wait	Avg. Assembly Wait Time for those who Wait	Avg. Number Wait for Assembly	Avg. Number Wait for Rinse	Avg. Number do not Wait for Assembly	Avg. Number do not Wait for Rinse
--	0.5	Baseline	25.28	50.90	202.25	17.22	30.87	105.34	85.66	126.09	106.38
60	0.5	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
600	0.5	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
3600	0.5	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
32400	0.5	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
60	0.6	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
600	0.6	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
3600	0.6	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
32400	0.6	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
60	0.7	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
600	0.7	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
3600	0.7	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
32400	0.7	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
60	0.8	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
600	0.8	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
3600	0.8	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
32400	0.8	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
60	0.9	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
600	0.9	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
3600	0.9	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
32400	0.9	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
60	1	10	24.50	50.23	200.87	16.20	30.74	102.53	81.42*	130.33*	109.18
600	1	13	23.80*	50.09	200.18	15.13*	31.20	99.55*	78.95*	132.52*	111.32*
3600	1	15	24.08*	49.53	199.71*	15.68*	29.61	103.03	80.41*	130.70*	107.78
32400	1	15	24.08*	49.53	199.71*	15.68*	29.61	103.03	80.41*	130.70*	107.78

Table 33: BAMQ Root Mean Square Results (all times are in minutes)

Run Time (Seconds)	a _s Weight	Serial Number	Avg. Rinse Station Time	Avg. Assembly Station Time	Avg. Turnaround Time	Avg. Rinse Wait Time for those who Wait	Avg. Assembly Wait Time for those who Wait	Avg. Number Wait for Assembly	Avg. Number Wait for Rinse	Avg. Number do not Wait for Assembly	Avg. Number do not Wait for Rinse
--	0.5	Baseline	25.28	50.90	202.25	17.22	30.87	105.34	85.66	126.09	106.38
60	0.5	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
600	0.5	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
3600	0.5	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
32400	0.5	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
60	0.6	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
600	0.6	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
3600	0.6	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
32400	0.6	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
60	0.7	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
600	0.7	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
3600	0.7	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
32400	0.7	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
60	0.8	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
600	0.8	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
3600	0.8	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
32400	0.8	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
60	0.9	1	24.88	49.86	200.93	16.71	30.06	103.00	83.97	127.79	108.65
600	0.9	21	24.52	50.39	201.01	17.54	32.56	102.63	82.84	128.70*	107.63
3600	0.9	8	24.85	50.64	201.56	17.18	32.20	103.35	82.83	127.46	106.29
32400	0.9	5	24.81	51.08	201.99	17.41	32.35	103.27	81.83*	129.67*	107.74
60	1	9	24.59	50.78	201.59	16.60	31.66	102.52*	81.02*	130.77	108.92
600	1	14	24.24*	50.96	201.53	15.86	31.66	104.31	80.85*	130.77*	107.29
3600	1	18	24.85	51.62	202.86	17.44	33.41	102.49	80.87*	131.41*	109.73*
32400	1	18	24.85	51.62	202.86	17.44	33.41	102.49	80.87*	131.41*	109.73*

Table 34: BAMLGPD and 2BAMLGPD Simulation Results (all times are in minutes)

Run Time (Seconds)	a _s Weight	Serial Number	Avg. Rinse Station Time	Avg. Assembly Station Time	Avg. Turnaround Time	Avg. Rinse Wait Time for those who Wait	Avg. Assembly Wait Time for those who Wait	Avg. Number Wait for Assembly	Avg. Number Wait for Rinse	Avg. Number do not Wait for Assembly	Avg. Number do not Wait for Rinse
--	0.5	Baseline	25.28	50.90	202.25	17.22	30.87	105.34	85.66	126.09	106.38
60	0.5	22	23.98*	49.96	200.13*	15.50*	30.22	102.41	80.29*	132.21*	110.02*
600	0.5	23	23.96*	49.09*	199.37*	15.51*	28.74	100.40*	78.91*	133.04*	111.50*
3600	0.5	23	23.96*	49.09*	199.37*	15.51*	28.74	100.40*	78.91*	133.04*	111.50*
32400	0.5	23	23.96*	49.09*	199.37*	15.51*	28.74	100.40*	78.91*	133.04*	111.50*
60	0.6	24	24.50*	49.91	200.62	16.29	30.72	101.15	81.70*	130.77*	111.27*
600	0.6	23	23.96*	49.09*	199.37*	15.51*	28.74	100.40*	78.91*	133.04*	111.50*
3600	0.6	23	23.96*	49.09*	199.37*	15.51*	28.74	100.40*	78.91*	133.04*	111.50*
32400	0.6	23	23.96*	49.09*	199.37*	15.51*	28.74	100.40*	78.91*	133.04*	111.50*
60	0.7	25	23.64*	47.67*	197.61*	14.91*	27.03*	96.49*	76.33*	134.61*	114.21*
600	0.7	23	23.96*	49.09*	199.37*	15.51*	28.74	100.40*	78.91*	133.04*	111.50*
3600	0.7	23	23.96*	49.09*	199.37*	15.51*	28.74	100.40*	78.91*	133.04*	111.50*
32400	0.7	23	23.96*	49.09*	199.37*	15.51*	28.74	100.40*	78.91*	133.04*	111.50*
60	0.8	26	23.74*	49.08*	199.07*	14.84*	28.63	100.37*	79.19*	132.48*	110.94*
600	0.8	23	23.96*	49.09*	199.37*	15.51*	28.74	100.40*	78.91*	133.04*	111.50*
3600	0.8	23	23.96*	49.09*	199.37*	15.51*	28.74	100.40*	78.91*	133.04*	111.50*
32400	0.8	23	23.96*	49.09*	199.37*	15.51*	28.74	100.40*	78.91*	133.04*	111.50*
60	0.9	26	23.74*	49.08*	199.07*	14.84*	28.63	100.37*	79.19*	132.48*	110.94*
600	0.9	23	23.96*	49.09*	199.37*	15.51*	28.74	100.40*	78.91*	133.04*	111.50*
3600	0.9	27	23.74*	48.77*	198.79*	14.69*	27.65*	101.51	79.49*	132.85*	110.72*
32400	0.9	27	23.74*	48.77*	198.79*	14.69*	27.65*	101.51	79.49*	132.85*	110.72*
60	1	28	23.67*	48.87*	198.84*	14.68*	27.88*	100.23*	78.34*	132.93*	110.86*
600	1	29	24.41*	50.50	201.24	16.37	31.87	100.97*	80.30*	132.01*	111.35*
3600	1	30	24.81	50.58	201.71	17.09	31.50	102.52	81.63*	130.50*	109.57*
32400	1	31	24.36*	48.90*	199.57*	16.75	29.98	98.25*	79.21*	131.13*	111.62*
60	1	32 (2 PH)	24.49	49.44	200.21	16.59	29.37	101.12	80.12*	132.60*	111.36*
600	1	32 (2 PH)	24.49	49.44	200.21	16.59	29.37	101.12	80.12*	132.60*	111.36*
3507.86	1	32 (2 PH)	24.49	49.44	200.21	16.59	29.37	101.12	80.12*	132.60*	111.36*

Table 35: Number of Statistically Significant Metric Improvements by Model

Model	A_s Weight						Total	% Rate
	0.5	0.6	0.7	0.8	0.9	1		
BAMQ Quadratic	0	0	0	10	30	22	62	29%
BAMQ Linear Square	0	0	0	0	20	20	40	19%
BAMQ Log	0	0	0	0	0	18	18	8%
BAMQ Root Mean Square	0	0	0	0	3	11	14	6%
BAMLGPD	30	28	33	32	32	24	179	83%
2BAMLGPD	--	--	--	--	--	12	--	33%

Table 35 suggests that within BAMQ, the quadratic and linear square $S_{ii'}$ calculation techniques are most effective. This confirms the results from chapter 4. BAMLGPD has more metric improvements than the four BAMQ models combined. This also confirms the results from chapter 4 suggesting BAMLGPD is a more effective model. In particular, BAMLGPD performs well across all of the a_s weights, whereas the BAMQ models do not perform well until the a_s weight is 0.9 or 1. BAMLGPD also performs well across all run times. In fact, the single biggest improvement in average case turnaround time, 197.61 minutes, occurs with BAMLGPD a_s weight 0.7, run time 60 seconds. While an improvement of 4.64 minutes from the 202.25 minute baseline schedule may not seem large, consider that the SPD processes approximately 234 cases during a normal workweek. This would result in approximately 1,085.76 minutes, or about 2.26 SPD staff shifts, less than the SPD currently spends processing cases each week.

One factor that was not accounted for in the block assignment models is the schedule of each surgical group. The models did not account for the expected timing of OR case arrivals to the SPD for different surgical group combinations. As an extreme example, consider two different schedules. In schedule one, the first case for the seven surgical groups is expected to last approximately one hour for each group, resulting in seven cases arriving to the SPD at approximately the same time. This would result in significant delays in SPD case processing. Contrast that with schedule two, in which the first case for the seven surgical groups last from 60 minutes to 150 minutes incrementing every 15

minutes, resulting in a nice evenly spaced case arrival rate to the SPD. This schedule is much easier for the SPD to process and would have much fewer cases waiting in line than the first schedule.

Although the larger number of simulation replications helps reduce the effect of this noise on the simulation results, an additional set of schedules was created and simulated to control for this effect. These schedules, referred to as “stack” schedules, were created for each schedule generated in chapter four along with the historical baseline schedule. Within each surgical group, surgeries are scheduled to start one minute after the preceding surgery’s scheduled start time. Each surgical case takes one minute for the OR to complete and the OR turnover time is also one minute. Essentially, all of the surgical cases for the day are processed within the first 10-15 minutes and ‘stack” on top of one another at the SPD entrance. Additionally, non-elective cases and non-OR cases do not exist. Thus, the stack schedules are a truer version of what the block assignment models specifically address in the objective function SPD cost term. Theoretically, the block assignment models should show better improvement with the stack schedules.

Table 36 displays the number of statistically significant metric improvements by model with the stack schedules. For the stack schedules, the four metrics relating to the number of cases that wait and do not wait at the rinse and assembly queues is going to be high regardless of schedule and were not counted. Essentially, the same methodology as figure 22 was followed except the bottom 4 metrics were not measured. Therefore, there were only five metrics for each simulation run and a total of 120 possible instances of metric improvement for each model.

All the models performed better with the stacked schedules. In particular, the BAMQ models performed much better at lower a_s values. This result makes sense because the stack schedules are a more accurate depiction of what the block assignment models actually minimize with the total SPD cost term. This does not mean the models are any more effective in practice because the concept of a stack schedule is not realistic. Furthermore, it would be very difficult for a block assignment model to address the expected timing of cases to the SPD. However, it is encouraging to see the models

perform better (as they should) with the stack schedules. Additionally, BAMLGPD still emerges as the best model, further suggesting it is a more robust model than BAMQ.

Table 36: Number of Statistically Significant Metric Improvements by Model, Stack Schedules

	A _s Weight							
Model	0.5	0.6	0.7	0.8	0.9	1	Total	% Rate
BAMQ Quadratic	16	16	16	12	16	16	92	77%
BAMQ Linear Square	16	16	16	16	20	18	102	85%
BAMQ Log	16	16	16	16	16	20	100	83%
BAMQ Root Mean Square	16	16	16	16	14	14	92	77%
BAMLGPD	18	18	20	20	20	18	114	95%
2BAMLGPD	--	--	--	--	--	12	--	60%

Section 5: TOM Results

The nature of the TOM study in chapter five prevents a direct simulation comparison like the block assignment models in chapter four. While there was a baseline expected annual instrument utilization rate that compared to the TOM results, there was no baseline schedule that could be compared within the simulation model. However, this research study investigated the potential impact more efficient preference cards could have on the SPD performance.

Efficient preference cards decrease the number of unused instruments that SPD staff sterilize. This decrease in workload would affect the rinsing and assembly stations in the SPD. Thus, this research study conducted a design of experiment in which all the rinsing and assembly probability distributions were decreased from 5-20%, incrementing every 5%. Table 37 displays these results, along with the original baseline simulation metrics. Like the block assignment model schedule simulations, a 95% confidence interval of the metric difference was calculated to determine statistical significance. All the results in table 37 are statistically significant improvements over the baseline historical schedule.

Table 37: Effect of Reduction in Rinse and Assembly Times on SPD Performance

	AVG Rinse Station Time	Avg Assembly Station Time	Avg Turnaround Time	Avg Rinse Wait Time for those who Wait	Avg Assembly Wait Time for those who Wait	Avg Number Wait for Assembly	Avg Number Wait for Rinse	Avg Number do not Wait for Assembly	Avg Number do not Wait for Rinse
Baseline Schedule	25.28	50.90	202.25	17.22	30.87	105.34	85.66	126.09	106.38
5% Reduction	22.74	46.35	195.15	14.76	27.25	97.94	78.20	133.90	114.16
10% Reduction	20.65	42.29	188.91	12.83	24.41	89.33	70.71	140.83	122.20
15% Reduction	19.17	37.94	183.02	11.70	20.64	80.29	66.28	145.58	131.58
20 % Reduction	17.49	34.55	177.76	10.53	18.16	72.39	58.93	153.80	140.33

Figures 23 and 24 display the linear relationship between the percent reduction and SPD turnaround, rinse, and assembly time metrics. Figure 24 shows a larger decrease in the assembly time versus rinse time as the percentage reduction increases. This result agrees with the direct observations of the SPD, in which SPD staff in the rinse station often did not scrub unused instruments. However, SPD staff did handle all instruments regardless of whether they were used during the assembly process. Therefore, reducing the number of unused instruments would have a larger impact on the assembly process than the rinsing process.

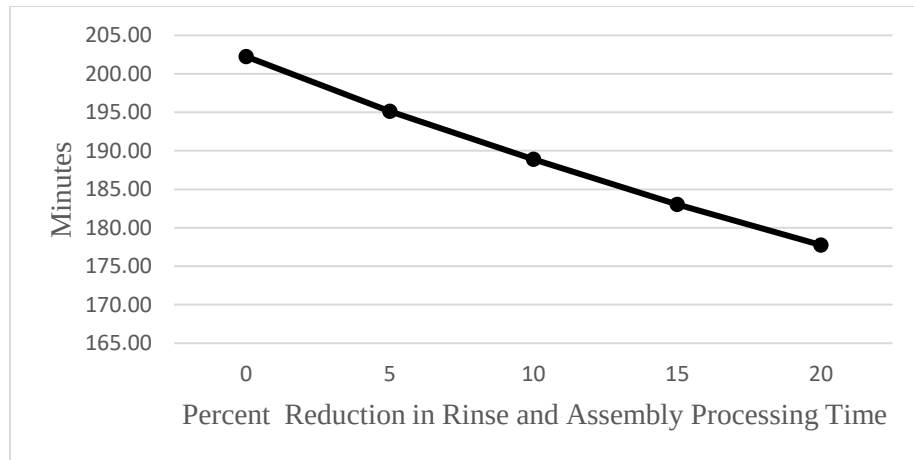


Figure 23: SPD Case Turnaround Time vs. Reduction in Rinse and Assembly Time

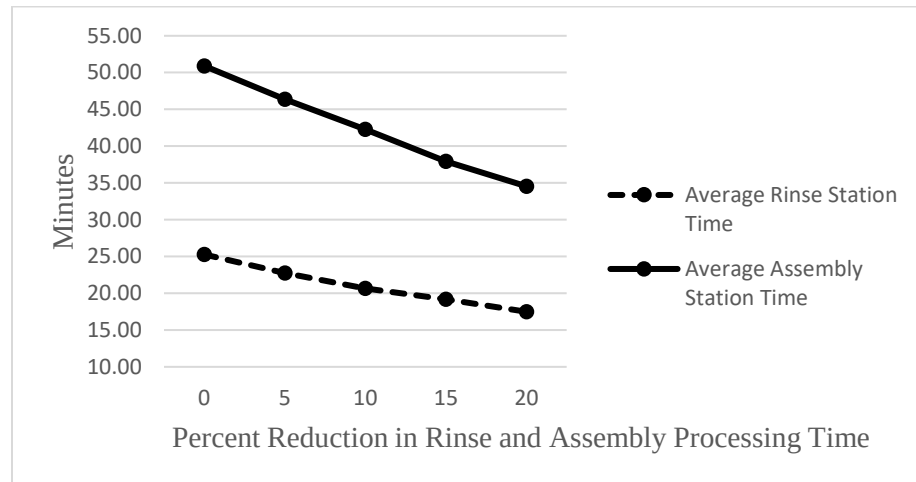


Figure 24: Average Rinse and Assembly Station Time vs. Reduction in Rinse and Assembly Time

The TOP simulation results suggest that, given the structure of the observed SPD and the estimated parameters for this research study, reducing the number of unused instruments is a more effective way to improve SPD performance than rearranging the block schedule. A relatively small percentage reduction in the rinsing and assembly processing times yielded larger improvement in the SPD simulation metrics than the most optimal block assignment model. For example, a 5% reduction in rinse and assembly processing time produced an average case turnaround time of 195.15 minutes, compared to the 197.61 minutes from the best performing block schedule.

The simulation results, along with SPD direct observations, also suggest that reducing SPD staff turnover is a more effective and practical method to improve SPD performance than rearranging the block schedule. During the SPD observations, a new SPD staff member was in the training process of rinsing and assembling cases. This new SPD staff member often took twice as long to process cases than more experienced staff. Though it was outside the scope of this research study, there was a clear learning curve associated with rinsing and assembling the different types of cases and trays. Furthermore, it appeared that it would take several weeks (if not months) before a new SPD staff member could process all types of cases and trays as quickly as more experienced staff. Therefore, reducing the amount of staff turnover would decrease the average rinse and assembly

processing times of the SPD staff. The TOM simulation results demonstrated even relatively small reductions in these processing times improves SPD performance better than rearranging the block schedule.

Section 6: Chapter Summary

The two research hypotheses in this study included developing a comprehensive simulation model to test the results of the mathematical models from chapters four and five. In this chapter, a simulation model of the OR and SPD was developed, verified, and validated similar to [108]. A baseline historical schedule based on a BHDH dataset from January 2018 – June 2018 was generated. Then, the block assignment model schedules from chapter four were simulated along with the baseline historical schedule. Nine metrics of interest from the simulation results of the baseline and research model schedules were compared for statistical significance. “Stack” schedules were then generated to control for differences within surgical group schedules and five of the original nine metrics of interest were compared for statistical significance with the baseline stack schedule. The simulation results closely follow the findings from chapter four. Key findings include:

- BAMLGPD is the more effective model than BAMQ, with an impressive 83% metric improvement rate
- Within BAMQ, the quadratic and linear square calculation techniques were more effective than log and root mean square (29% and 19% improvement rates versus 8% and 6% improvement rates, respectively)
- BAMQ stack schedules performed much better, though BAMLGPD still had the best % improvement rate of the stack schedules (95% compared to a maximum of 85% with BAMQ – linear square)

The TOM in chapter five did not produce schedules comparable to the historical baseline like the chapter four models. Instead, the TOM improves preference cards, which reduces SPD rinsing and assembly processing times. These processing time probability distributions were systemically decreased, and the baseline schedule was then simulated with the decreased processing times. The results were then compared for statistical significance to the baseline schedule simulation with the original processing times. Key findings include:

- A mere 5% reduction in processing times significantly improved all nine metrics more than the best of all the block schedules from chapter four
- A linear relationship emerged between percent reduction in processing time and improvement in SPD case turnaround time
- The same percentage reduction had a larger impact on assembly processing time compared to rinse processing time, which agreed with direction observation of the SPD
- The results suggest reducing SPD staff turnover is a more effective and practical method for improving SPD performance than rearranging the OR block schedule

Several opportunities for future research surrounding the simulation model exist. The variability oriented sequencing rules from [134] could be simulated again to determine their impact on the SPD. The variability oriented sequencing rules could also be applied to the chapter four schedules to determine the effect on both patient-centered OR metrics (number and magnitude of late starts) and SPD metrics. More generally, the simulation model could be used to examine the impact any schedule has on patient-centered metrics and SPD metrics. Downstream units such as the Post Anesthesia Care Unit could also be incorporated into the model.

CHAPTER SEVEN

CONCLUSIONS

Thesis Summary

This research study conducted a comprehensive literature review of technical OR scheduling articles and articles surrounding the SPD (chapter two). Then, the study developed three block assignment models that considered surgical group preferences and SPD cost (chapter four). Next, the study developed a goal programming tray optimization model that addresses the TOP. Finally, the study developed a comprehensive simulation model of an OR suite and its SPD to test the results of the previously developed mathematical models (chapter 6).

Chapter two reviewed all technical OR scheduling papers beginning where the most recent literature review concluded. The review covered 113 articles from 2015 to April 2018. It utilized the same classification scheme as the previous literature review and added a new category, geographic location. Table 11 summarizes the findings of the literature review. One of the most notable findings of the literature review was that incorporating the SPD into scheduling models had only been done once. Thus, this research study developed scheduling models that incorporate the SPD to help fill this research gap.

This research study then conducted a smaller literature review focusing on OR instrument preference cards and the SPD. The secondary literature review found that preference cards are often inefficient and that the TOP is an emerging research problem. It also found only three SPD simulation model articles (two of which could actually be considered one research study by the same authors). Based upon the results of the literature review, the study proposed the following hypotheses:

Sterilization department hypothesis (H₁): Despite its critical role in the OR surgery process, researchers and practitioners have not accounted for the SPD when developing long term scheduling strategies as they have for other upstream and downstream resources [28, 159]. Consequently, an important dynamic is missing in the existing mathematical scheduling models and strategies. A block assignment model that considers SPD workload can improve SPD performance. A comprehensive simulation model incorporating the SPD can test the block assignment model results.

Preference card hypothesis (H₂): OR preference cards, which designate what instruments are in what trays and what trays are assigned to a given surgical procedure, are often inefficient. This results in a substantial percentage of instruments and trays going unused during procedures. The unnecessarily high number of instruments going through the SPD decreases the daily SPD throughput, which can cause delays in subsequent OR surgery start times or affect how surgeries are scheduled. A goal programming model can improve preference cards. This will result in better SPD throughput. A comprehensive simulation model can test the goal programming model results.

In chapter four, this research study developed three models that determine an OR suite's block schedule by maximizing surgical group preferences and minimizing the SPD cost. The first model, BAMQ, had a quadratic objective with four different techniques for calculating the SPD cost terms in the SPD workload matrix. The SPD cost was defined as the total expected processing time for the manual stations within the SPD. This research study conducted a systematic model evaluation plan for the BAMQ that altered objective weights, model run time, and calculation techniques. Of the four calculation techniques, the two quadratic techniques performed better than the log and root mean square techniques.

After identifying a correlation between a smoother SPD input across different days and SPD cost, the research study developed two goal programming models that more directly addressed this

dynamic. The BAMLGPD made the same decision as the BAMQ, but the SPD cost was altered to represent the total daily deviation from the overall weekly average. The BAMLGPD was a completely linear formulation. The research study conducted a model evaluation plan for the BAMLGPD similar to BAMQ and found that the BAMLGPD outperformed the BAMQ. Finally, a third model, 2BAMLGPD, split the BAMLGPD into two phases. The first phase minimized the SPD cost while the second phase maximized surgical group preferences. The 2BAMLGPD is limited in terms of applicability because the first phase essentially gives all of the weight to the SPD cost. However, it could serve as a useful way to quickly find a lower bound on the total BAMLGPD SPD cost.

In chapter five, the research study developed a TOM to solve the TOP. It was the first TOP model that incorporated expected non-usage rates instead of assuming that all instrument requests must be met. After generating parameters based off BHDH data and previous TOP articles, the research study conducted a model evaluation plan that altered several model parameters. The model successfully increased the expected annual utilization rate and produced several intuitive results. Now that the model appears to do what is supposed to do after the computational results, several areas for future research exist.

In chapter six, the research study developed a discrete event simulation model of an OR suite and its SPD. The simulation model was used to test the results of the mathematical models in chapters four and five. The simulation model confirmed the results in chapter four, which found that the BAMLGPD outperformed the BAMQ. The simulation model found that relatively small decreases in rinsing and assembly processing times yielded better SPD performance than rearranging the block schedule.

Practical Applications

The research study results provide insights to OR managers. These include:

- Reducing SPD staff turnover and/or making minor improvements to OR preference cards are a more practical and effective way to improve SPD performance than rearranging the block schedule
- If OR managers are considering changes to the OR block schedule or creating a new block schedule and want to consider the impact on the SPD, they should try to level the anticipated SPD workload across the different blocks. This does not necessarily require running a mathematical model. Potential heuristics and guidelines that level SPD workload include:
 - Categorize the surgical groups into different buckets depending on their normal caseload size (volume and complexity). Then, attempt to assign approximately the same number of surgical groups from each bucket to every block.
 - Use a similar categorization scheme as above and rank the buckets in order of caseload size. Then, try to assign block times such that the sum of the ranks for each block is within one or two of all the other block times. For example, consider the scenario for the chapter four models where an OR suite has seven ORs and one block time per weekday. The surgical groups are placed in one of three buckets. The largest groups are placed in bucket one, the medium size groups in bucket two, and the small groups in bucket three. Assuming there are approximately the same number of groups in each bucket, assign block time such that the sum of the assigned buckets for each weekday is between 12 and 16 (the average total daily caseload size would be 7 ORs multiplied by an average bucket size of 2 which equals 14).
 - Let n equal the number of block times in the planning horizon, take the largest n or $n-1$ surgical groups and assign them all different block times. For example, in the chapter four scenario, take the four or five largest surgical groups and assign them to different weekdays.

- If the OR block schedule cannot be leveled across time blocks because of other restrictions, consider having additional SPD staff during heavier block times and less SPD staff during lighter block times.
- If an OR suite has a block schedule but in practice the surgical groups often swap block times, then try to encourage swaps between similar sized surgical groups so that the anticipated SPD workload does not substantially deviate from what was planned.

Microsoft Excel provides a simple but useful platform for OR managers to explore how altering the block schedule affects SPD workload. The OR manager only needs a groups' C_i value, which can be as simple as a rank order or bucket classification, and can then formulate a schedule that automatically displays the SPD workload across different blocks.

Future Work

Opportunities for future research include addressing the research study's assumptions and limitations. For chapter 4, these are:

- Extending the block assignment models to OR suite settings that utilize an open or modified block system
- Systematically altering the range of surgical group caseload values (C_i) to see how this affects model improvement over the baseline schedule
- Systemically running the models for a longer time to see how much the relative MIP gap decreases
- Develop heuristics for the models to reduce computation time
- Systematically altering the problem size to see how this affects model performance

- Incorporate expected end time of surgical cases and their arrival into the SPD
- Relax the assumption of consistent SPD staffing throughout the time horizon

For the chapter 5 TOM, these are:

- Conduct a longitudinal study that collects instrument preference and usage data from a real world setting and apply the model to that scenario. This would also allow researchers to determine if the patient demographic and surgeon demographic independence assumptions are valid or not
- Systematically altering problem size to see how this affects model performance
- Further refining the PA_{ip} and PC_t parameters
- Relax the fixed inventory assumption
- Develop a heuristic to reduce computation time
- Incorporated the daily schedule and total tray capacity into a more comprehensive model

The simulation model was developed to test the results of the mathematical models. In all these areas for future research, the simulation model could be updated as necessary to account for changes to the study (e.g. altering SPD staff schedules).

The opportunities for future work based on the model assumptions and limitations that are highlighted in this section provide plenty of areas for researchers to explore. Given that the TOP is a relatively new research problem, addressing the model assumptions and limitations in future work will provide plenty of new knowledge to this field. The OR scheduling problem, however, has been explored in great detail by researchers for the last couple decades. For this type of research problem, it is also important to think about future work from a broader perspective and examine what direction future research programs may take so that new knowledge can be added.

Looking at the OR scheduling literature review summary (table 11), one of the broader trends that emerged was the increase in model complexity. This can come from multiple categories in table 11, whether it is considering a new upstream/downstream unit, several upstream/downstream units simultaneously, new performance measures, or several performance measures simultaneously. This research study's primary contribution to new knowledge in the field was incorporating an element of the OR system, the SPD, that had only been considered once before in OR scheduling models. One of the primary areas for future work now lies in considering other upstream/downstream units along with this new element in OR scheduling models. For example, is there an inherent conflict between considering the needs of the SPD and recovery ward? This research study found that spreading out the complex surgical groups throughout the week helps SPD performance. However, complex caseloads may tend to have longer post-surgery patient stays in the recovery ward. For recovery wards that are short staffed on weekends, it may be difficult to spread out complex caseloads to the end of the week because that would strain weekend recovery ward capacity.

Research Conclusions

The research objectives of this study were met:

1. Examine and improve how block scheduling for an OR suite affects the SPD.
 - The results from chapters four and six clearly demonstrate that a block schedule impacts SPD performance. Certain block schedules resulted in significantly better SPD performance than others.
2. Examine and improve preference cards for surgical cases
 - The results from chapter five show that a mathematical goal programming model can improve preference card efficiency

The results from chapters four and six confirmed the first research hypothesis. **A block assignment model, BAMLGPD, which considered SPD workload, improved SPD performance.**

The results from chapters five and six confirmed the second research hypothesis. **A goal programming model improved preference cards, resulting in better SPD throughput.**

In summary, this research successfully met its objectives and confirmed its hypotheses. This research is among the first of its kind to consider SPD workload as an objective in OR block scheduling models. This research is the first to consider expected instrument non-usage rates in the tray optimization problem. Finally, this research is among the first of its kind to develop a comprehensive simulation model of an OR suite and its SPD to test the results of mathematical models. From a more generalizable perspective, this research study demonstrates the importance of incorporating elements in a system that may not initially be considered important. Studying the overlooked element in a system can yield valuable insights about that element's true impact as well as better understanding of the entire system.

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APPENDICES

APPENDIX A

BLOCK ASSIGNMENT MODEL CODE

BAMQ 2ND OBJECTIVE TERM DERIVATION

For each day [$\sum_k()$], sum a surgical group's binary decision variables across all ORs (j index) to see if a surgical group is assigned to that day. Then, check all possible surgical group combinations by multiplying the sum of two sets of binary decision variables and the groups' corresponding s_{ir} value:

$$\begin{aligned}
 & (X_{111} + X_{121} + X_{131} + X_{141} + X_{151} + X_{161} + X_{171} + X_{181}) * (X_{111} + X_{121} + X_{131} + X_{141} + X_{151} + X_{161} + X_{171} + X_{181}) * S_{11} + \\
 & (X_{111} + X_{121} + X_{131} + X_{141} + X_{151} + X_{161} + X_{171} + X_{181}) * (X_{211} + X_{221} + X_{231} + X_{241} + X_{251} + X_{261} + X_{271} + X_{281}) * S_{12} + \\
 & (X_{111} + X_{121} + X_{131} + X_{141} + X_{151} + X_{161} + X_{171} + X_{181}) * (X_{311} + X_{321} + X_{331} + X_{341} + X_{351} + X_{361} + X_{371} + X_{381}) * S_{13} + \\
 & \dots \\
 & (X_{111} + X_{121} + X_{131} + X_{141} + X_{151} + X_{161} + X_{171} + X_{181}) * (X_{111} + X_{121} + X_{131} + X_{141} + X_{151} + X_{161} + X_{171} + X_{181}) * S_{11} + \\
 & (X_{211} + X_{221} + X_{231} + X_{241} + X_{251} + X_{261} + X_{271} + X_{281}) * (X_{211} + X_{221} + X_{231} + X_{241} + X_{251} + X_{261} + X_{271} + X_{281}) * S_{22} + \\
 & (X_{211} + X_{221} + X_{231} + X_{241} + X_{251} + X_{261} + X_{271} + X_{281}) * (X_{311} + X_{321} + X_{331} + X_{341} + X_{351} + X_{361} + X_{371} + X_{381}) * S_{23} + \\
 & \dots \\
 & (X_{211} + X_{221} + X_{231} + X_{241} + X_{251} + X_{261} + X_{271} + X_{281}) * (X_{111} + X_{121} + X_{131} + X_{141} + X_{151} + X_{161} + X_{171} + X_{181}) * S_{21} + \\
 & \dots \\
 & (X_{111} + X_{121} + X_{131} + X_{141} + X_{151} + X_{161} + X_{171} + X_{181}) * (X_{111} + X_{121} + X_{131} + X_{141} + X_{151} + X_{161} + X_{171} + X_{181}) * S_{ii}
 \end{aligned}$$

Then, factor out left hand side:

$$\begin{aligned}
 & (X_{111} + X_{121} + X_{131} + X_{141} + X_{151} + X_{161} + X_{171} + X_{181}) [(X_{111} + X_{121} + X_{131} + X_{141} + X_{151} + X_{161} + X_{171} + X_{181}) * S_{11} + \\
 & (X_{211} + X_{221} + X_{231} + X_{241} + X_{251} + X_{261} + X_{271} + X_{281}) * S_{12} + \dots (X_{111} + X_{121} + X_{131} + X_{141} + X_{151} + X_{161} + X_{171} + X_{181}) * S_{11}] \\
 & + \\
 & (X_{211} + X_{221} + X_{231} + X_{241} + X_{251} + X_{261} + X_{271} + X_{281}) [(X_{211} + X_{221} + X_{231} + X_{241} + X_{251} + X_{261} + X_{271} + X_{281}) * S_{22} + \\
 & (X_{311} + X_{321} + X_{331} + X_{341} + X_{351} + X_{361} + X_{371} + X_{381}) * S_{23} + \dots (X_{111} + X_{121} + X_{131} + X_{141} + X_{151} + X_{161} + X_{171} + X_{181}) * S_{11}] + \\
 & \dots \\
 & (X_{111} + X_{121} + X_{131} + X_{141} + X_{151} + X_{161} + X_{171} + X_{181}) * (X_{111} + X_{121} + X_{131} + X_{141} + X_{151} + X_{161} + X_{171} + X_{181}) * S_{ii}
 \end{aligned}$$

Finally, abbreviate with summation notation

$$\begin{aligned}
 & a_s (\sum_k (\\
 & \sum_j x_{1jk} [(\sum_j x_{1jk}) S_{1,1} + (\sum_j x_{2jk}) S_{1,2} + \dots (\sum_j x_{Ijk}) S_{1,I}] + \\
 & \sum_j x_{2jk} [(\sum_j x_{2jk}) S_{2,2} + (\sum_j x_{3jk}) S_{2,3} + \dots (\sum_j x_{Ijk}) S_{2,I}] + \\
 & \dots \\
 & \sum_j x_{Ijk} [(\sum_j x_{Ijk}) S_{I,I}]))
 \end{aligned}$$

BAMQ AMPL CODE

AMPL has two primary types of files. “Model” or .mod files describe the mathematical formulation.

“Data” or .dat files are used for large data parameters. Each line of code ends with a “;”.

Multiple lines are combined for brevity. The following is the model file for BAMQ:

```

param I := 35; param J := 7; param K := 5; set GROUP = 1..I; set OR = 1..J; set DAY = 1..K;
var x{i in GROUP, j in OR, k in DAY} binary; param P{i in GROUP, j in OR, k in DAY};

```

param S1 {i in 1..I}; param S2 {i in 2..I}; param S3 {i in 3..I}; param S4 {i in 4..I}; param S5 {i in 5..I}; param
 S6 {i in 6..I}; param S7 {i in 7..I}; param S8 {i in 8..I}; param S9 {i in 9..I}; param S10 {i in 10..I}; param
 S11 {i in 11..I}; param S12 {i in 12..I}; param S13 {i in 13..I}; param S14 {i in 14..I}; param S15 {i in
 15..I}; param S16 {i in 16..I}; param S17 {i in 17..I}; param S18 {i in 18..I}; param S19 {i in 19..I}; param
 S20 {i in 20..I}; param S21 {i in 21..I}; param S22 {i in 22..I}; param S23 {i in 23..I}; param S24 {i in
 24..I}; param S25 {i in 25..I}; param S26 {i in 26..I}; param S27 {i in 27..I}; param S28 {i in 28..I}; param
 S29 {i in 29..I}; param S30 {i in 30..I}; param S31 {i in 31..I}; param S32 {i in 32..I}; param S33 {i in
 33..I}; param S34 {i in 34..I}; param S35 {i in 35..I}; param as default 0.5; param asstep := 0.1;
 minimize obj: (1-as) * sum{i in GROUP, j in OR, k in DAY}{P[i,j,k]*x[i,j,k]} + as * sum{k in DAY}
 (sum{j in OR}{x[1,j,k]}*(sum{l in OR}{x[1,l,k]}*S1[1]+ sum{l in OR}{x[2,l,k]}*S1[2]+ sum{l in
 OR}{x[3,l,k]}*S1[3]+sum{l in OR}{x[4,l,k]}*S1[4]+sum{l in OR}{x[5,l,k]}*S1[5]+sum{l in
 OR}{x[6,l,k]}*S1[6]+sum{l in OR}{x[7,l,k]}*S1[7]+sum{l in OR}{x[8,l,k]}*S1[8]+sum{l in
 OR}{x[9,l,k]}*S1[9]+sum{l in OR}{x[10,l,k]}*S1[10]+sum{l in OR}{x[11,l,k]}*S1[11]+sum{l in
 OR}{x[12,l,k]}*S1[12]+sum{l in OR}{x[13,l,k]}*S1[13]+sum{l in OR}{x[14,l,k]}*S1[14]+sum{l in
 OR}{x[15,l,k]}*S1[15]+sum{l in OR}{x[16,l,k]}*S1[16]+sum{l in OR}{x[17,l,k]}*S1[17]+sum{l in
 OR}{x[18,l,k]}*S1[18]+sum{l in OR}{x[19,l,k]}*S1[19]+sum{l in OR}{x[20,l,k]}*S1[20]+sum{l in
 OR}{x[21,l,k]}*S1[21]+sum{l in OR}{x[22,l,k]}*S1[22]+sum{l in OR}{x[23,l,k]}*S1[23]+sum{l in
 OR}{x[24,l,k]}*S1[24]+sum{l in OR}{x[25,l,k]}*S1[25]+sum{l in OR}{x[26,l,k]}*S1[26]+sum{l in
 OR}{x[27,l,k]}*S1[27]+sum{l in OR}{x[28,l,k]}*S1[28]+sum{l in OR}{x[29,l,k]}*S1[29]+sum{l in
 OR}{x[30,l,k]}*S1[30]+sum{l in OR}{x[31,l,k]}*S1[31]+sum{l in OR}{x[32,l,k]}*S1[32]+sum{l in
 OR}{x[33,l,k]}*S1[33]+sum{l in OR}{x[34,l,k]}*S1[34]+sum{l in OR}{x[35,l,k]}*S1[35]) + sum{j in
 OR}{x[2,j,k]}*(sum{l in OR}{x[2,l,k]}*S2[2]+sum{l in OR}{x[3,l,k]}*S2[3]+sum{l in
 OR}{x[4,l,k]}*S2[4]+sum{l in OR}{x[5,l,k]}*S2[5]+sum{l in OR}{x[6,l,k]}*S2[6]+sum{l in
 OR}{x[7,l,k]}*S2[7]+sum{l in OR}{x[8,l,k]}*S2[8]+sum{l in OR}{x[9,l,k]}*S2[9]+sum{l in
 OR}{x[10,l,k]}*S2[10]+sum{l in OR}{x[11,l,k]}*S2[11]+sum{l in OR}{x[12,l,k]}*S2[12]+sum{l in
 OR}{x[13,l,k]}*S2[13]+sum{l in OR}{x[14,l,k]}*S2[14]+sum{l in OR}{x[15,l,k]}*S2[15]+sum{l in
 OR}{x[16,l,k]}*S2[16]+sum{l in OR}{x[17,l,k]}*S2[17]+sum{l in OR}{x[18,l,k]}*S2[18]+sum{l in
 OR}{x[19,l,k]}*S2[19]+sum{l in OR}{x[20,l,k]}*S2[20]+sum{l in OR}{x[21,l,k]}*S2[21]+sum{l in
 OR}{x[22,l,k]}*S2[22]+sum{l in OR}{x[23,l,k]}*S2[23]+sum{l in OR}{x[24,l,k]}*S2[24]+sum{l in
 OR}{x[25,l,k]}*S2[25]+sum{l in OR}{x[26,l,k]}*S2[26]+sum{l in OR}{x[27,l,k]}*S2[27]+sum{l in
 OR}{x[28,l,k]}*S2[28]+sum{l in OR}{x[29,l,k]}*S2[29]+sum{l in OR}{x[30,l,k]}*S2[30]+sum{l in
 OR}{x[31,l,k]}*S2[31]+sum{l in OR}{x[32,l,k]}*S2[32]+sum{l in OR}{x[33,l,k]}*S2[33]+sum{l in
 OR}{x[34,l,k]}*S2[34]+sum{l in OR}{x[35,l,k]}*S2[35]) + sum{j in OR}{x[3,j,k]}*(sum{l in
 OR}{x[3,l,k]}*S3[3]+sum{l in OR}{x[4,l,k]}*S3[4]+sum{l in OR}{x[5,l,k]}*S3[5]+sum{l in
 OR}{x[6,l,k]}*S3[6]+sum{l in OR}{x[7,l,k]}*S3[7]+sum{l in OR}{x[8,l,k]}*S3[8]+sum{l in
 OR}{x[9,l,k]}*S3[9]+sum{l in OR}{x[10,l,k]}*S3[10]+sum{l in OR}{x[11,l,k]}*S3[11]+sum{l in
 OR}{x[12,l,k]}*S3[12]+sum{l in OR}{x[13,l,k]}*S3[13]+sum{l in OR}{x[14,l,k]}*S3[14]+sum{l in
 OR}{x[15,l,k]}*S3[15]+sum{l in OR}{x[16,l,k]}*S3[16]+sum{l in OR}{x[17,l,k]}*S3[17]+sum{l in
 OR}{x[18,l,k]}*S3[18]+sum{l in OR}{x[19,l,k]}*S3[19]+sum{l in OR}{x[20,l,k]}*S3[20]+sum{l in
 OR}{x[21,l,k]}*S3[21]+sum{l in OR}{x[22,l,k]}*S3[22]+sum{l in OR}{x[23,l,k]}*S3[23]+sum{l in
 OR}{x[24,l,k]}*S3[24]+sum{l in OR}{x[25,l,k]}*S3[25]+sum{l in OR}{x[26,l,k]}*S3[26]+sum{l in
 OR}{x[27,l,k]}*S3[27]+sum{l in OR}{x[28,l,k]}*S3[28]+sum{l in OR}{x[29,l,k]}*S3[29]+sum{l in
 OR}{x[30,l,k]}*S3[30]+sum{l in OR}{x[31,l,k]}*S3[31]+sum{l in OR}{x[32,l,k]}*S3[32]+sum{l in
 OR}{x[33,l,k]}*S3[33]+sum{l in OR}{x[34,l,k]}*S3[34]+sum{l in OR}{x[35,l,k]}*S3[35]) + sum{j in
 OR}{x[4,j,k]}*(sum{l in OR}{x[4,l,k]}*S4[4]+sum{l in OR}{x[5,l,k]}*S4[5]+sum{l in
 OR}{x[6,l,k]}*S4[6]+sum{l in OR}{x[7,l,k]}*S4[7]+sum{l in OR}{x[8,l,k]}*S4[8]+sum{l in
 OR}{x[9,l,k]}*S4[9]+sum{l in OR}{x[10,l,k]}*S4[10]+sum{l in OR}{x[11,l,k]}*S4[11]+sum{l in
 OR}{x[12,l,k]}*S4[12]+sum{l in OR}{x[13,l,k]}*S4[13]+sum{l in OR}{x[14,l,k]}*S4[14]+sum{l in
 OR}{x[15,l,k]}*S4[15]+sum{l in OR}{x[16,l,k]}*S4[16]+sum{l in OR}{x[17,l,k]}*S4[17]+sum{l in
 OR}{x[18,l,k]}*S4[18]+sum{l in OR}{x[19,l,k]}*S4[19]+sum{l in OR}{x[20,l,k]}*S4[20]+sum{l in
 OR}{x[21,l,k]}*S4[21]+sum{l in OR}{x[22,l,k]}*S4[22]+sum{l in OR}{x[23,l,k]}*S4[23]+sum{l in
 OR}{x[24,l,k]}*S4[24]+sum{l in OR}{x[25,l,k]}*S4[25]+sum{l in OR}{x[26,l,k]}*S4[26]+sum{l in
 OR}{x[27,l,k]}*S4[27]+sum{l in OR}{x[28,l,k]}*S4[28]+sum{l in OR}{x[29,l,k]}*S4[29]+sum{l in
 OR}{x[30,l,k]}*S4[30]+sum{l in OR}{x[31,l,k]}*S4[31]+sum{l in OR}{x[32,l,k]}*S4[32]+sum{l in

[illegible]


```

OR}{x[28,j,k]}*(sum{1 in OR}{x[28,l,k]}*S28[28]+sum{1 in OR}{x[29,l,k]}*S28[29]+sum{1 in
OR}{x[30,l,k]}*S28[30]+sum{1 in OR}{x[31,l,k]}*S28[31]+sum{1 in OR}{x[32,l,k]}*S28[32]+sum{1 in
OR}{x[33,l,k]}*S28[33]+sum{1 in OR}{x[34,l,k]}*S28[34]+sum{1 in OR}{x[35,l,k]}*S28[35]+sum{j in
OR}{x[29,j,k]}*(sum{1 in OR}{x[29,l,k]}*S29[29]+sum{1 in OR}{x[30,l,k]}*S29[30]+sum{1 in
OR}{x[31,l,k]}*S29[31]+sum{1 in OR}{x[32,l,k]}*S29[32]+sum{1 in OR}{x[33,l,k]}*S29[33]+sum{1 in
OR}{x[34,l,k]}*S29[34]+sum{1 in OR}{x[35,l,k]}*S29[35]+sum{j in OR}{x[30,j,k]}*(sum{1 in
OR}{x[30,l,k]}*S30[30]+sum{1 in OR}{x[31,l,k]}*S30[31]+sum{1 in OR}{x[32,l,k]}*S30[32]+sum{1 in
OR}{x[33,l,k]}*S30[33]+sum{1 in OR}{x[34,l,k]}*S30[34]+sum{1 in OR}{x[35,l,k]}*S30[35]+sum{j in
OR}{x[31,j,k]}*(sum{1 in OR}{x[31,l,k]}*S31[31]+sum{1 in OR}{x[32,l,k]}*S31[32]+sum{1 in
OR}{x[33,l,k]}*S31[33]+sum{1 in OR}{x[34,l,k]}*S31[34]+sum{1 in OR}{x[35,l,k]}*S31[35]+sum{j in
OR}{x[32,j,k]}*(sum{1 in OR}{x[32,l,k]}*S32[32]+sum{1 in OR}{x[33,l,k]}*S32[33]+sum{1 in
OR}{x[34,l,k]}*S32[34]+sum{1 in OR}{x[35,l,k]}*S32[35]+ sum{j in OR}{x[33,j,k]}*(sum{1 in
OR}{x[33,l,k]}*S33[33]+sum{1 in OR}{x[34,l,k]}*S33[34]+sum{1 in OR}{x[35,l,k]}*S33[35]+ sum{j in
OR}{x[34,j,k]}*(sum{1 in OR}{x[34,l,k]}*S34[34]+sum{1 in OR}{x[35,l,k]}*S34[35]+ sum{j in
OR}{x[35,j,k]}*(sum{1 in OR}{x[35,l,k]}*S35[35]));

```

subject to weeklygroupconstraint $\{i \text{ in GROUP}\}: \text{sum}\{k \text{ in DAY}, j \text{ in OR}\}(x[i,j,k]) = 1;$

subject to roomassignedconstraint $\{k \text{ in DAY}, j \text{ in OR}\}: \text{sum}\{i \text{ in GROUP}\} (x[i,j,k]) = 1;$

The following is the BAMQ product data file. The other three files (linear square, log, root mean square) have the same structure but different S_{ij} values.

data;

param: S1 S2 S3 S4 S5 S6 S7 S8 S9 S10 S11 S12 S13 S14 S15 S16 S17 S18 S19 S20 S21 S22 S23 S24 S25
S26 S27 S28 S29 S30 S31 S32 S33 S34 S35 :=

[illegible]

28	1.641.91	1.33	1.37	1.70	1.19	1.59	1.61	1.30	1.48	1.33	1.31	1.39
	1.49	1.07	1.45	1.33	1.62	2.25	1.92	1.75	1.47	1.07	1.07	2.61
	1.30	1.37	1.65	.	.	.	.	.	.	.	.	.
29	1.842.19	1.44	1.49	1.92	1.25	1.78	1.80	1.39	1.64	1.43	1.41	1.51
	1.64	1.10	1.59	1.44	1.81	2.63	2.20	1.98	1.62	1.09	1.10	3.11
	1.39	1.48	1.85	2.11	.	.	.	.	.	.	.	.
30	2.202.70	1.62	1.70	2.31	1.35	2.11	2.14	1.56	1.91	1.62	1.59	1.73
	1.92	1.15	1.84	1.62	2.16	3.32	2.71	2.40	1.89	1.13	1.15	4.00
	1.56	1.69	2.21	2.58	3.25	.	.	.	.	.	.	.
31	1.802.13	1.41	1.46	1.87	1.23	1.74	1.76	1.37	1.60	1.41	1.39	1.48
	1.61	1.09	1.55	1.41	1.77	2.54	2.14	1.93	1.59	1.09	1.09	3.00
	1.37	1.46	1.80	2.05	2.50	2.00	.	.	.	.	.	.
32	1.231.32	1.11	1.13	1.25	1.06	1.21	1.21	1.10	1.17	1.11	1.11	1.13
	1.17	1.02	1.15	1.11	1.22	1.44	1.32	1.26	1.16	1.02	1.02	1.57
	1.10	1.13	1.23	1.30	1.43	1.28	1.08	.	.	.	.	.
33	1.451.64	1.23	1.26	1.50	1.13	1.42	1.43	1.21	1.34	1.23	1.22	1.27
	1.34	1.05	1.31	1.23	1.44	1.88	1.65	1.53	1.33	1.05	1.05	2.14
	1.21	1.26	1.46	1.60	1.86	1.57	1.16	1.32	.	.	.	.
34	1.601.85	1.31	1.35	1.66	1.17	1.56	1.57	1.28	1.45	1.31	1.29	1.36
	1.46	1.07	1.42	1.31	1.58	2.17	1.86	1.70	1.44	1.06	1.07	2.51
	1.28	1.34	1.61	1.79	2.13	1.75	1.21	1.43	1.57	.	.	.
35	1.331.47	1.17	1.19	1.36	1.09	1.30	1.31	1.15	1.25	1.17	1.16	1.20
	1.25	1.03	1.23	1.17	1.32	1.64	1.47	1.39	1.24	1.03	1.03	1.83
	1.15	1.19	1.33	1.44	1.62	1.41	1.11	1.23	1.31	1.17;	.	.

param P:=

[*,*,1]: 1 2 3 4 5 6 7 :=

1	3	3	3	1	2	2	2
2	3	3	3	1	2	2	2
3	3	3	3	1	2	2	2
4	3	3	3	1	2	2	2
5	4	4	4	4	3	4	4
6	3	1	3	3	3	3	2
7	3	1	3	3	3	3	2
8	3	1	3	3	3	3	2
9	3	1	3	3	3	3	2
10	4	3	4	4	4	4	4
11	4	3	4	4	4	4	4
12	4	4	4	4	4	3	4
13	3	2	3	3	1	3	3
14	3	2	3	3	1	3	3
15	1	3	3	3	3	3	3
16	4	4	4	3	4	4	4
17	3	2	1	2	2	2	1
18	3	2	1	2	2	2	1
19	3	2	1	2	2	2	1
20	3	2	1	2	2	2	1
21	3	2	1	2	2	2	1
22	3	2	1	2	2	2	1
23	3	4	4	4	4	4	4
24	3	4	4	4	4	4	4
25	5	4	4	4	4	3	4
26	3	5	5	5	5	5	5
27	3	5	5	5	5	5	5
28	5	5	5	3	4	4	4

29	4	4	4	4	4	4	4		
30	100	100	100	100	3	100	100		
31	100	100	100	100	3	100	100		
32	3	3	3	2	2	1	2		
33	5	4	4	4	4	4	3		
34	5	4	4	4	4	4	3		
35	5	4	4	4	4	4	3		
[*,*],2]: 1		2	3	4	5	6		7	:=
1	5	5	5	5	5	5	5		
2	5	5	5	5	5	5	5		
3	5	5	5	5	5	5	5		
4	5	5	5	5	5	5	5		
5	3	3	3	2	1	2	2		
6	3	2	3	3	3	3	1		
7	3	2	3	3	3	3	1		
8	3	2	3	3	3	3	1		
9	3	2	3	3	3	3	1		
10	4	3	4	4	4	4	4		
11	4	3	4	4	4	4	4		
12	4	4	4	4	4	3	4		
13	4	3	4	4	3	4	4		
14	4	3	4	4	3	4	4		
15	3	4	4	4	4	4	4		
16	4	4	4	3	4	4	4		
17	3	1	2	2	2	2	2		
18	3	1	2	2	2	2	2		
19	3	1	2	2	2	2	2		
20	3	1	2	2	2	2	2		
21	3	1	2	2	2	2	2		
22	3	1	2	2	2	2	2		
23	3	4	4	4	4	4	4		
24	3	4	4	4	4	4	4		
25	5	4	4	4	4	3	4		
26	3	5	5	5	5	5	5		
27	1	3	3	3	3	3	3		
28	3	3	3	1	2	2	2		
29	2	2	1	2	2	2	2		
30	100	100	100	100	3	100	100		
31	100	100	100	100	3	100	100		
32	5	4	4	4	4	3	4		
33	3	3	3	2	2	1	2		
34	3	3	3	2	2	1	2		
35	3	3	3	2	2	1	2		
[*,*],3]: 1		2	3	4	5	6		7	:=
1	3	3	3	1	2	2	2		
2	3	3	3	1	2	2	2		
3	3	3	3	1	2	2	2		
4	3	3	3	1	2	2	2		
5	4	4	4	4	3	4	4		
6	4	4	4	4	4	4	4		
7	4	4	4	4	4	4	4		
8	4	4	4	4	4	4	4		
9	4	4	4	4	4	4	4		
10	4	3	4	4	4	4	4		

11	4	3	4	4	4	4	4
12	4	4	4	4	4	3	4
13	3	1	3	3	2	3	3
14	3	1	3	3	2	3	3
15	3	4	4	4	4	4	4
16	3	2	2	2	1	2	2
17	3	2	1	2	2	2	2
18	3	2	1	2	2	2	2
19	3	2	1	2	2	2	2
20	3	2	1	2	2	2	2
21	3	2	1	2	2	2	2
22	3	2	1	2	2	2	2
23	3	4	4	4	4	4	4
24	1	3	3	3	3	3	3
25	3	3	3	2	2	1	2
26	3	5	5	5	5	5	5
27	3	5	5	5	5	5	5
28	5	5	5	3	4	4	4
29	4	4	4	4	4	4	4
30	100	100	100	100	3	100	100
31	100	100	100	100	3	100	100
32	5	4	4	4	4	3	4
33	3	3	3	2	2	2	1
34	3	3	3	2	2	2	1
35	3	3	3	2	2	2	1
[*,* ,4]: 1			2	3	4	5	6
1	3	3	3	1	2	2	2
2	3	3	3	1	2	2	2
3	3	3	3	1	2	2	2
4	3	3	3	1	2	2	2
5	4	4	4	4	3	4	4
6	3	2	3	3	3	3	1
7	3	2	3	3	3	3	1
8	3	2	3	3	3	3	1
9	3	2	3	3	3	3	1
10	2	1	2	2	2	2	2
11	2	1	2	2	2	2	2
12	4	4	4	4	4	3	4
13	4	3	4	4	3	4	4
14	4	3	4	4	3	4	4
15	3	4	4	4	4	4	4
16	4	4	4	3	4	4	4
17	3	2	1	2	2	2	2
18	3	2	1	2	2	2	2
19	3	2	1	2	2	2	2
20	3	2	1	2	2	2	2
21	3	2	1	2	2	2	2
22	3	2	1	2	2	2	2
23	3	4	4	4	4	4	4
24	3	4	4	4	4	4	4
25	5	4	4	4	4	3	4
26	1	3	3	4	4	4	4
27	3	5	5	5	5	5	5
28	5	5	5	3	4	4	4

7

:=

```

29 4 4 4 4 4 4 4
30 100 100 100 100 1 100 100
31 100 100 100 100 1 100 100
32 5 4 4 4 4 3 4
33 5 4 4 4 4 1 3
34 5 4 4 4 4 1 3
35 5 4 4 4 4 1 3
[*,*,5]: 1 2 3 4 5 6 7 :=
1 3 3 3 1 2 2 2
2 3 3 3 1 2 2 2
3 3 3 3 1 2 2 2
4 3 3 3 1 2 2 2
5 4 4 4 4 3 4 4
6 3 2 3 3 3 3 1
7 3 2 3 3 3 3 1
8 3 2 3 3 3 3 1
9 3 2 3 3 3 3 1
10 2 1 2 2 2 2 2
11 2 1 2 2 2 2 2
12 2 2 2 2 2 1 2
13 4 3 4 4 3 4 4
14 4 3 4 4 3 4 4
15 3 4 4 4 4 4 4
16 4 4 4 3 4 4 4
17 3 2 1 2 2 2 2
18 3 2 1 2 2 2 2
19 3 2 1 2 2 2 2
20 3 2 1 2 2 2 2
21 3 2 1 2 2 2 2
22 3 2 1 2 2 2 2
23 1 3 3 3 3 3 3
24 3 4 4 4 4 4 4
25 5 4 4 4 4 3 4
26 3 5 5 5 5 5 5
27 3 5 5 5 5 5 5
28 5 5 5 3 4 4 4
29 2 2 2 2 2 2 2
30 100 100 100 100 1 100 100
31 100 100 100 100 1 100 100
32 5 4 4 4 4 3 4
33 5 4 4 4 4 3 3
34 5 4 4 4 4 3 3
35 5 4 4 4 4 3 3;

```

BAMLGPD AMPL CODE

The following is the BAMLGPD model file:

```

param I := 35;
param K := 5;
param J := 7;
set GROUP = 1..I;
set DAY = 1..K;
set OR = 1..J;

```

```

var x{i in GROUP,j in OR,k in DAY} binary;
param P{i in GROUP, j in OR, k in DAY};
var deviationunder {k in DAY};
var deviationover {k in DAY};
param C{i in GROUP};
param as default 0.5;
param asstep := 0.1;
minimize obj:
(1-as) * sum{i in GROUP, j in OR, k in DAY}(P[i,j,k]*x[i,j,k])      +
as * sum {k in DAY}(deviationunder[k] + deviationover[k]);
subject to roomassignedconstraint {k in DAY, j in OR}: sum{i in GROUP}(x[i,j,k]) = 1;
subject to weeklygroupconstraint {i in GROUP}: sum{k in DAY, j in OR}(x[i,j,k]) = 1;
subject to deviationconstraint {k in DAY}: sum{i in GROUP, j in OR}(x[i,j,k]*C[i]) + deviationunder[k] -
deviationover[k] = 8546.3/5;
subject to deviationundernonnegativity{k in DAY}: deviationunder[k] >=0;
subject to deviationovernonnegativity{k in DAY}: deviationover[k] >=0;

```

The following is the BAMLGPD data file:

```

data;
param C :=
1  287.95
2  405.03
3  150.54
4  168.58
5  314.54
6  86.21
7  265.39
8  273.09
9  134.20
10 217.81
11 149.71
12 142.57
13 175.75
14 219.69
15 37.01
16 200.57
17 150.54
18 276.93
19 553.85
20 407.93
21 334.81
22 212.81
23 33.62
24 37.01
25 715.44
26 134.50
27 166.48
28 289.20
29 378.18
30 537.27
31 358.18
32 103.99
33 205.38

```

```

34 271.33
35 150.21;
param P:=
[*,*,1]: 1      2      3      4      5      6      7      :=
1  3  3      3      1      2      2      2
2  3  3      3      1      2      2      2
3  3  3      3      1      2      2      2
4  3  3      3      1      2      2      2
5  4  4      4      4      3      4      4
6  3  1      3      3      3      3      2
7  3  1      3      3      3      3      2
8  3  1      3      3      3      3      2
9  3  1      3      3      3      3      2
10 4  3      4      4      4      4      4
11 4  3      4      4      4      4      4
12 4  4      4      4      4      3      4
13 3  2      3      3      1      3      3
14 3  2      3      3      1      3      3
15 1  3      3      3      3      3      3
16 4  4      4      3      4      4      4
17 3  2      1      2      2      2      1
18 3  2      1      2      2      2      1
19 3  2      1      2      2      2      1
20 3  2      1      2      2      2      1
21 3  2      1      2      2      2      1
22 3  2      1      2      2      2      1
23 3  4      4      4      4      4      4
24 3  4      4      4      4      4      4
25 5  4      4      4      4      3      4
26 3  5      5      5      5      5      5
27 3  5      5      5      5      5      5
28 5  5      5      3      4      4      4
29 4  4      4      4      4      4      4
30 100 100    100    100    3      100    100
31 100 100    100    100    3      100    100
32 3  3      3      2      2      1      2
33 5  4      4      4      4      4      3
34 5  4      4      4      4      4      3
35 5  4      4      4      4      4      3
[*,*,2]: 1      2      3      4      5      6      7      :=
1  5  5      5      5      5      5      5
2  5  5      5      5      5      5      5
3  5  5      5      5      5      5      5
4  5  5      5      5      5      5      5
5  3  3      3      2      1      2      2
6  3  2      3      3      3      3      1
7  3  2      3      3      3      3      1
8  3  2      3      3      3      3      1
9  3  2      3      3      3      3      1
10 4  3      4      4      4      4      4
11 4  3      4      4      4      4      4
12 4  4      4      4      4      3      4
13 4  3      4      4      3      4      4
14 4  3      4      4      3      4      4

```

15	3	4	4	4	4	4	4	
16	4	4	4	3	4	4	4	
17	3	1	2	2	2	2	2	
18	3	1	2	2	2	2	2	
19	3	1	2	2	2	2	2	
20	3	1	2	2	2	2	2	
21	3	1	2	2	2	2	2	
22	3	1	2	2	2	2	2	
23	3	4	4	4	4	4	4	
24	3	4	4	4	4	4	4	
25	5	4	4	4	4	3	4	
26	3	5	5	5	5	5	5	
27	1	3	3	3	3	3	3	
28	3	3	3	1	2	2	2	
29	2	2	1	2	2	2	2	
30	100	100	100	100	3	100	100	
31	100	100	100	100	3	100	100	
32	5	4	4	4	4	3	4	
33	3	3	3	2	2	1	2	
34	3	3	3	2	2	1	2	
35	3	3	3	2	2	1	2	
[*,*,3]: 1			2	3	4	5	6	7 :=
1	3	3	3	1	2	2	2	
2	3	3	3	1	2	2	2	
3	3	3	3	1	2	2	2	
4	3	3	3	1	2	2	2	
5	4	4	4	4	3	4	4	
6	4	4	4	4	4	4	4	
7	4	4	4	4	4	4	4	
8	4	4	4	4	4	4	4	
9	4	4	4	4	4	4	4	
10	4	3	4	4	4	4	4	
11	4	3	4	4	4	4	4	
12	4	4	4	4	4	3	4	
13	3	1	3	3	2	3	3	
14	3	1	3	3	2	3	3	
15	3	4	4	4	4	4	4	
16	3	2	2	2	1	2	2	
17	3	2	1	2	2	2	2	
18	3	2	1	2	2	2	2	
19	3	2	1	2	2	2	2	
20	3	2	1	2	2	2	2	
21	3	2	1	2	2	2	2	
22	3	2	1	2	2	2	2	
23	3	4	4	4	4	4	4	
24	1	3	3	3	3	3	3	
25	3	3	3	2	2	1	2	
26	3	5	5	5	5	5	5	
27	3	5	5	5	5	5	5	
28	5	5	5	3	4	4	4	
29	4	4	4	4	4	4	4	
30	100	100	100	100	3	100	100	
31	100	100	100	100	3	100	100	
32	5	4	4	4	4	3	4	

33	3	3	3	2	2	2	1		
34	3	3	3	2	2	2	1		
35	3	3	3	2	2	2	1		
[*,* ,4]: 1			2	3	4	5	6	7	:=
1	3	3	3	1	2	2	2		
2	3	3	3	1	2	2	2		
3	3	3	3	1	2	2	2		
4	3	3	3	1	2	2	2		
5	4	4	4	4	3	4	4		
6	3	2	3	3	3	3	1		
7	3	2	3	3	3	3	1		
8	3	2	3	3	3	3	1		
9	3	2	3	3	3	3	1		
10	2	1	2	2	2	2	2		
11	2	1	2	2	2	2	2		
12	4	4	4	4	4	3	4		
13	4	3	4	4	3	4	4		
14	4	3	4	4	3	4	4		
15	3	4	4	4	4	4	4		
16	4	4	4	3	4	4	4		
17	3	2	1	2	2	2	2		
18	3	2	1	2	2	2	2		
19	3	2	1	2	2	2	2		
20	3	2	1	2	2	2	2		
21	3	2	1	2	2	2	2		
22	3	2	1	2	2	2	2		
23	3	4	4	4	4	4	4		
24	3	4	4	4	4	4	4		
25	5	4	4	4	4	3	4		
26	1	3	3	4	4	4	4		
27	3	5	5	5	5	5	5		
28	5	5	5	3	4	4	4		
29	4	4	4	4	4	4	4		
30	100	100	100	100	1	100	100		
31	100	100	100	100	1	100	100		
32	5	4	4	4	4	3	4		
33	5	4	4	4	4	1	3		
34	5	4	4	4	4	1	3		
35	5	4	4	4	4	1	3		
[*,* ,5]: 1			2	3	4	5	6	7	:=
1	3	3	3	1	2	2	2		
2	3	3	3	1	2	2	2		
3	3	3	3	1	2	2	2		
4	3	3	3	1	2	2	2		
5	4	4	4	4	3	4	4		
6	3	2	3	3	3	3	1		
7	3	2	3	3	3	3	1		
8	3	2	3	3	3	3	1		
9	3	2	3	3	3	3	1		
10	2	1	2	2	2	2	2		
11	2	1	2	2	2	2	2		
12	2	2	2	2	2	1	2		
13	4	3	4	4	3	4	4		
14	4	3	4	4	3	4	4		

15	3	4	4	4	4	4	4
16	4	4	4	3	4	4	4
17	3	2	1	2	2	2	2
18	3	2	1	2	2	2	2
19	3	2	1	2	2	2	2
20	3	2	1	2	2	2	2
21	3	2	1	2	2	2	2
22	3	2	1	2	2	2	2
23	1	3	3	3	3	3	3
24	3	4	4	4	4	4	4
25	5	4	4	4	4	3	4
26	3	5	5	5	5	5	5
27	3	5	5	5	5	5	5
28	5	5	5	3	4	4	4
29	2	2	2	2	2	2	2
30	100	100	100	100	1	100	100
31	100	100	100	100	1	100	100
32	5	4	4	4	4	3	4
33	5	4	4	4	4	3	3
34	5	4	4	4	4	3	3
35	5	4	4	4	4	3	3;

The following is the 2BAMLGPD phase one model file:

```

param I := 35;
param K := 5;
set GROUP = 1..I;
set DAY = 1..K;
var x{i in GROUP,k in DAY} binary;
var deviationunder {k in DAY};
var deviationover {k in DAY};
param C{i in GROUP};
minimize obj: sum {k in DAY}(deviationunder[k] + deviationover[k]);

subject to roomsassignedconstraint {k in DAY}: sum{i in GROUP}(x[i,k]) = 7;
subject to groupassignedconstraint {i in GROUP}: sum{k in DAY}(x[i,k]) = 1;
subject to deviationconstraint {k in DAY}: sum{i in GROUP}(x[i,k]*C[i]) + deviationunder[k] -
    deviationover[k] = 8546.3/5;
subject to deviationundernonnegativity{k in DAY}: deviationunder[k] >=0;
subject to deviationovernonnegativity{k in DAY}: deviationover[k] >=0;

```

In AMPL, the phase one x_{ik} solution was labeled as parameter S_{ik} for the phase two file. The following is the phase two BAMLGPD model file:

```

param I := 35;
param K := 5;
param J := 7;
set GROUP = 1..I;
set DAY = 1..K;
set OR = 1..J;
var x{i in GROUP,j in OR,k in DAY} binary;
param P{i in GROUP, j in OR, k in DAY};
param S{i in GROUP, k in DAY};
minimize obj: sum{i in GROUP, j in OR, k in DAY}(P[i,j,k]*x[i,j,k]);
subject to Phase1Constraint {i in GROUP, k in DAY}: sum{j in OR}(x[i,j,k]) = S[i,k];

```

subject to roomassignedconstraint $\{k \text{ in DAY}, j \text{ in OR}\}: \text{sum}\{i \text{ in GROUP}\}(x[i,j,k]) = 1;$

The 2BAMLGPD data files are the same as the BAMLGPD data file. Phase one 2BAMLGPD data file only contains the C_i parameter while the phase two 2BAMLGPD data file contains the P_{ijk} parameter and the S_{ik} parameter (which was the x_{ik} output from phase one).

APPENDIX B

TRAY OPTIMIZATION MODEL CODE

TRAY OPTIMIZATION MODEL

The following is the AMPL code for the TOP. Multiple lines are combined for brevity.

```

param I := 174; param P := 12; param T := 6;
set INSTRUMENT = 1..I; set PROCEDURE = 1..P; set TRAY = 1..T;
var y {t in TRAY, p in PROCEDURE} binary; var b {i in INSTRUMENT, t in TRAY} integer;
var q {i in INSTRUMENT, t in TRAY, p in PROCEDURE} integer;
var s1plus {t in TRAY}; var s1minus {t in TRAY};
var s2plus {i in INSTRUMENT, p in PROCEDURE} integer;
var s2minus {i in INSTRUMENT, p in PROCEDURE} integer;
param A {i in INSTRUMENT, p in PROCEDURE}; param W {i in INSTRUMENT};
param WT {t in TRAY}; param N {p in PROCEDURE};
param C {t in TRAY}; param S {i in INSTRUMENT};
param PC {t in TRAY}; param PA {i in INSTRUMENT, p in PROCEDURE};
param U {i in INSTRUMENT, p in PROCEDURE}; param SL {p in PROCEDURE};
param MC {t in TRAY}; param M := 10000;
param MO := 3; param MU := 3;
minimize obj:
    sum{p in PROCEDURE, t in TRAY, i in INSTRUMENT} (q[i,t,p]*U[i,p]*N[p]) +
    sum{t in TRAY} (PC[t]*s1plus[t]) + sum {i in INSTRUMENT, p in PROCEDURE}
    (s2minus[i,p]*PA[i,p]*N[p]);
subject to trayweightconstraint {t in TRAY}: sum{i in INSTRUMENT} (b[i,t]*W[i]) + WT[t] + s1minus[t] -
    s1plus[t] = C[t];
subject to preferencesconstraint {i in INSTRUMENT, p in PROCEDURE}: sum{t in TRAY} (q[i,t,p]) +
    s2minus[i,p] - s2plus[i,p] = A[i,p];
subject to inventoryconstraint {i in INSTRUMENT}: sum {t in TRAY} (b[i,t]) <= S[i];
subject to maxtrayweightconstraint {t in TRAY}: sum {i in INSTRUMENT} (b[i,t]*W[i]) + WT[t] <= MC[t] *
    C[t];
subject to linearize1constraint {t in TRAY, p in PROCEDURE}: sum{i in INSTRUMENT} (q[i,t,p]) <= y[t,p] *
    M;
subject to linearize2constraint {i in INSTRUMENT, t in TRAY, p in PROCEDURE}: q[i,t,p] <= b[i,t];
subject to lineareize3constraint {i in INSTRUMENT, t in TRAY, p in PROCEDURE}: b[i,t] <= q[i,t,p] - y[t,p]
    * M + M;
subject to excessstrayweightnonnegativity {t in TRAY}: s1plus [t] >=0;
subject to undertrayweightnonnegativity {t in TRAY}: s1minus [t] >=0;
subject to excesspreferencesnonnegativity {i in INSTRUMENT, p in PROCEDURE}: s2plus [i,p] >=0;
subject to underpreferencesnonnegativity {i in INSTRUMENT, p in PROCEDURE}: s2minus [i,p] >=0;
subject to instrumentnonnegativity {i in INSTRUMENT, t in TRAY}: b[i,t] >= 0;
subject to linearizenonnegativity {i in INSTRUMENT, t in TRAY, p in PROCEDURE}: q[i,t,p] >=0;
subject to maxexcesspreferencedeviation {i in INSTRUMENT, p in PROCEDURE}: s2plus [i,p] <= MO;
subject to maxunderpreferencedeviation {i in INSTRUMENT, p in PROCEDURE}: s2minus [i,p] <= MU;
The data file for the TOM follows the same format as the data files in Appendix A. Due to the
    excessively large nature of the data file, it is omitted for brevity.

```

APPENDIX C

SIMULATION MODEL SCREENSHOTS

SIMULATION MODEL

Figure C-1 shows a screenshot of the entire simulation model in Arena. The five subsections will be shown in more detail in the following figures.

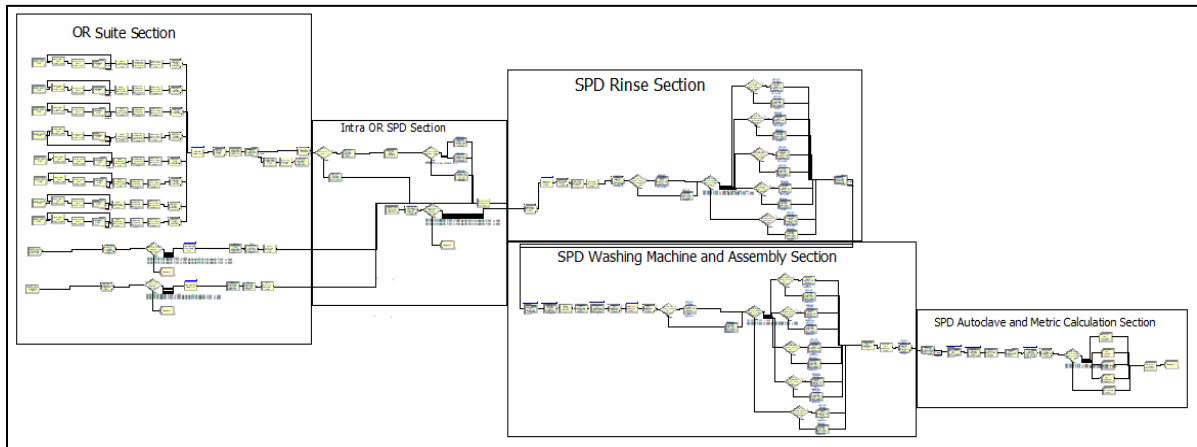


Figure C-2 displays the OR suite subsection. In this section, the surgical cases entities are created from the excel schedule file (elective cases) or generated according to their historical arrival rate (non-elective cases). Non-elective cases that occur outside of normal working hours are immediately disposed while the cases that occur during workhours are put in the OR queue with a higher priority than elective cases. Non-elective labor and delivery cases can only be process by OR 1. After a surgical case is processed, one cloned entity is created to account for the OR turnover while the original entity proceeds to the SPD.

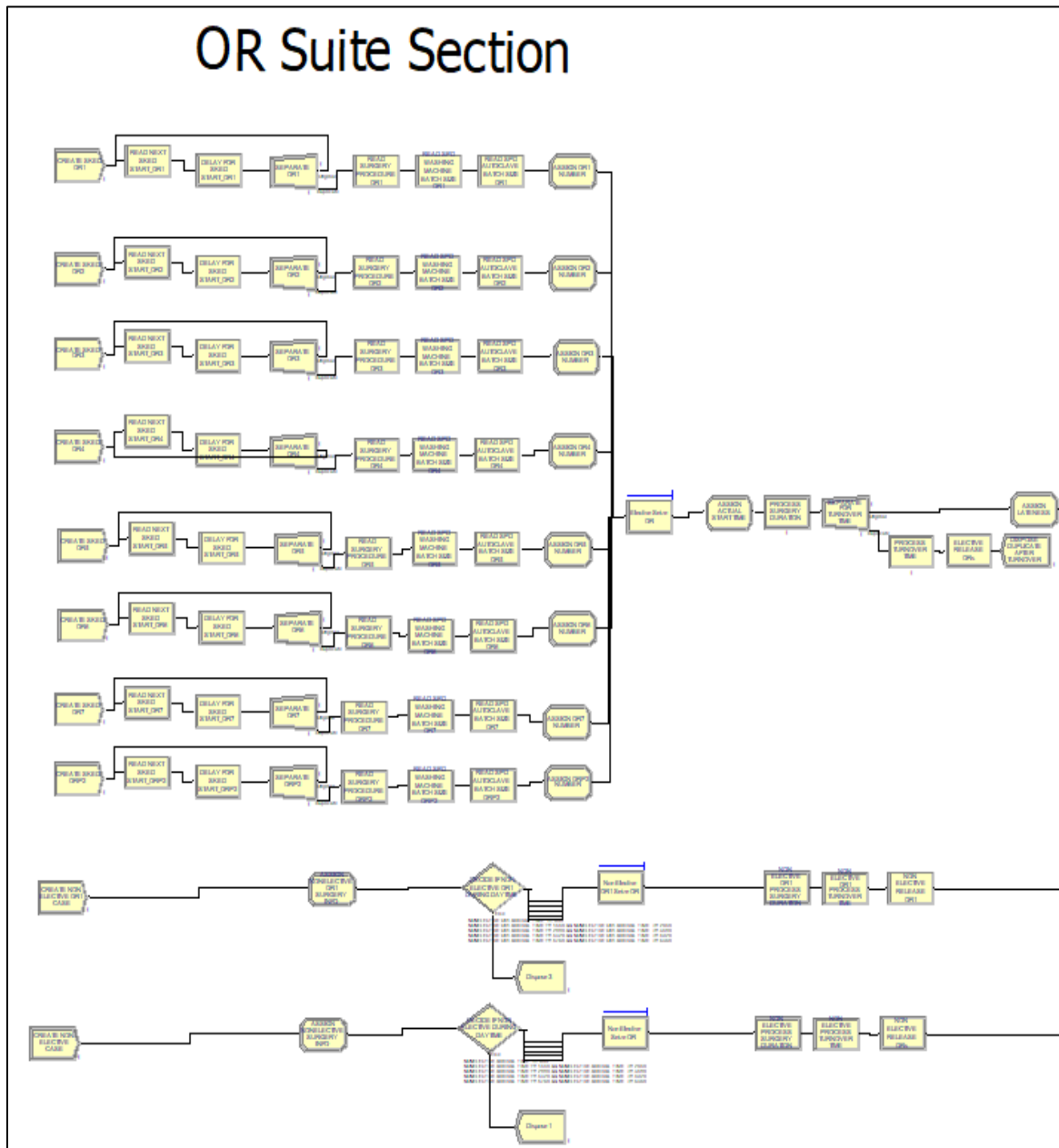
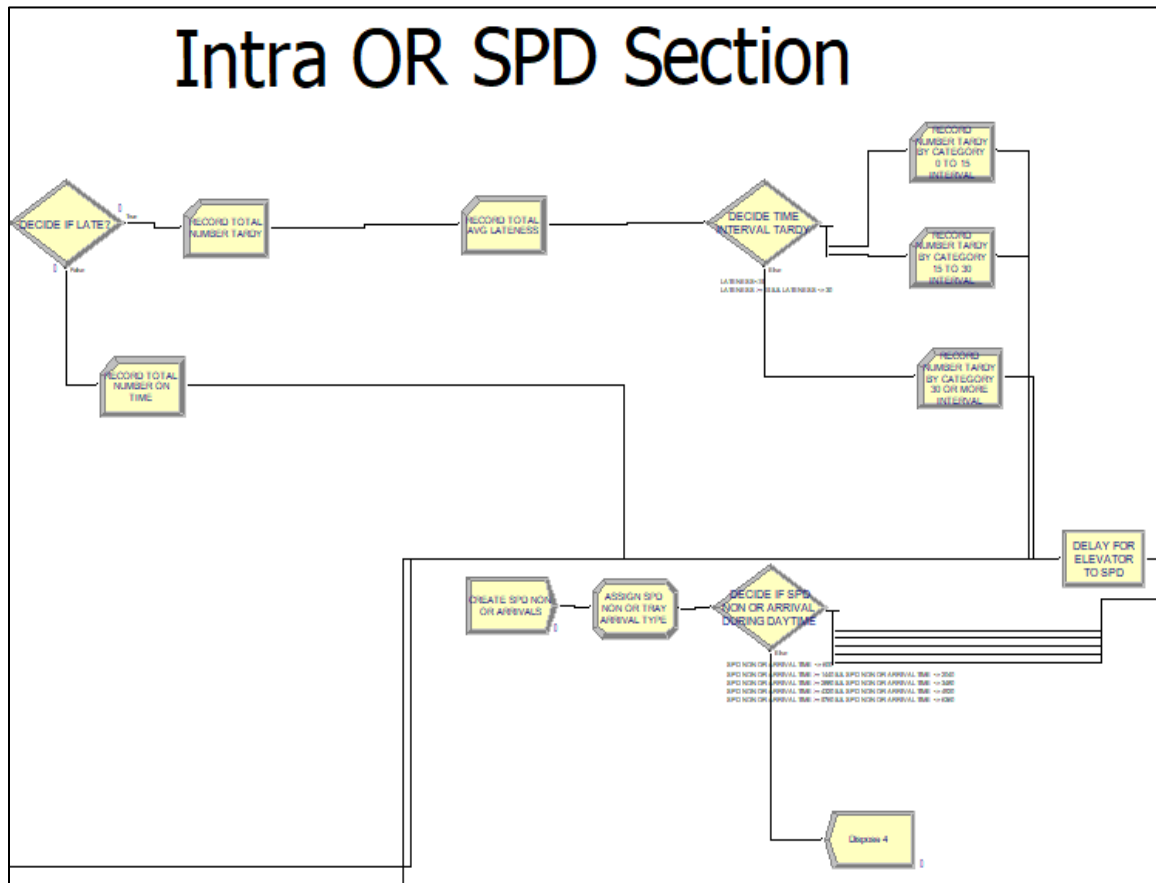
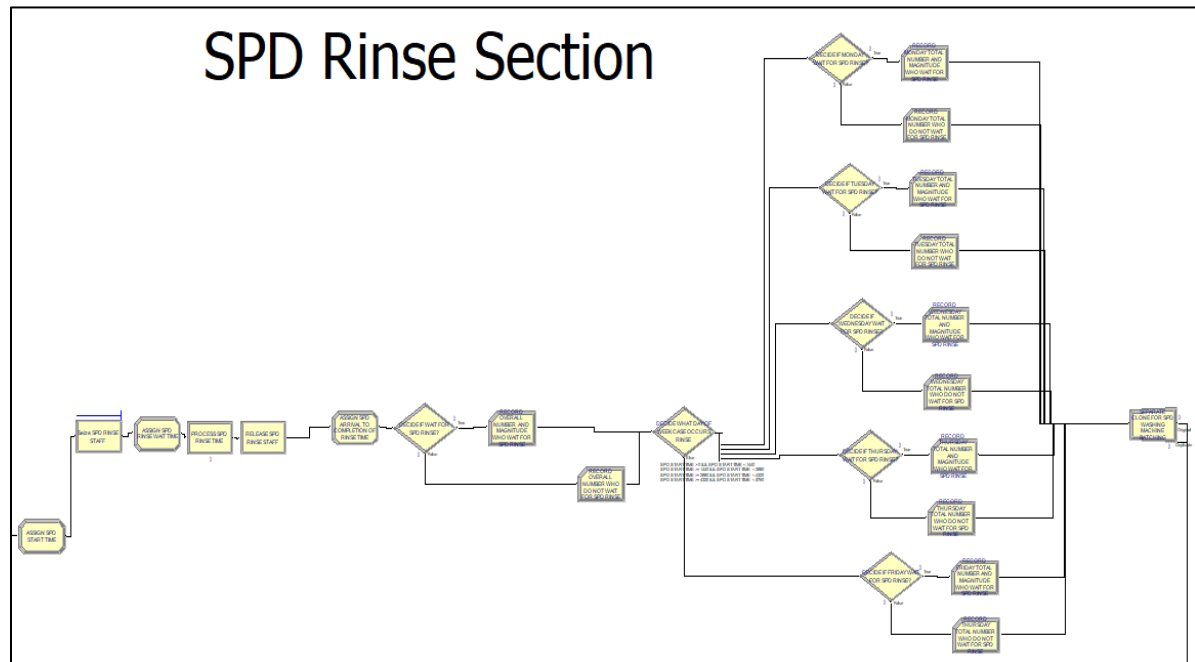


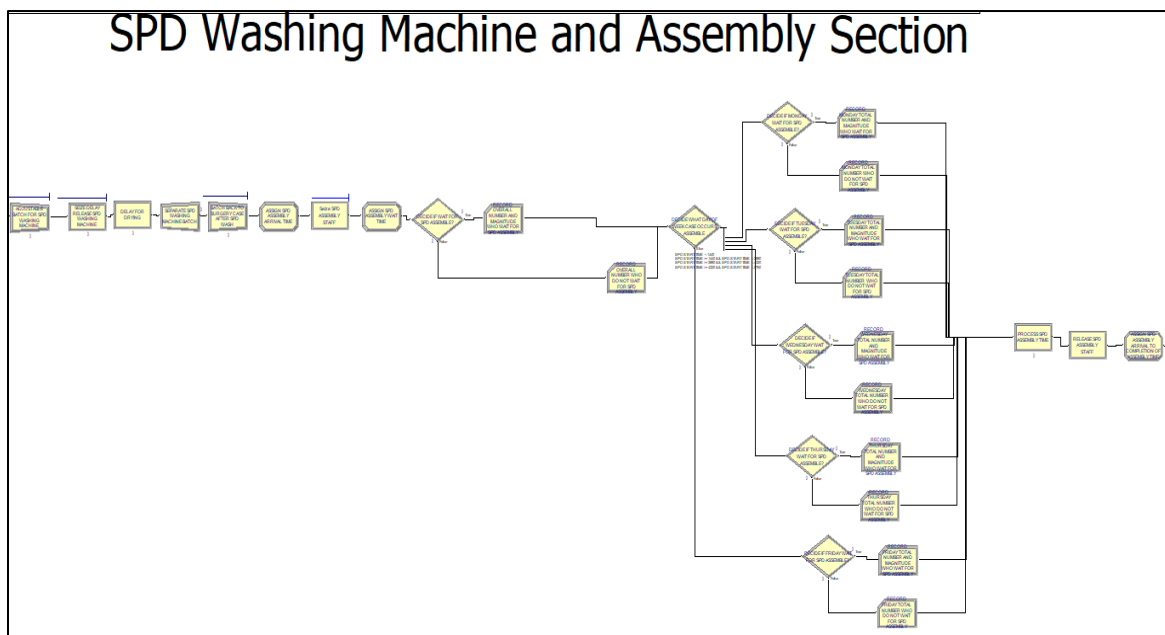
Figure C-3 displays the intra SPD OR section. The original model's metric calculations for number and magnitude of tardy surgeries remains in the new model. After which, elective cases are sent to the elevator to the SPD. Non-OR SPD cases are generated according to their historical arrival rate. Non-OR SPD cases arriving outside normal workhours are immediately disposed.



Section C-4 displays the SPD rinse section. Cases seize one of two SPD staff for manually rinsing. SPD rinse related metrics are calculated globally and by separate weekday, after which the cases are cloned for the washing machine batching.



Section C-5 displays the SPD washing machine and assembly section. Cases are batched and sent through the washing machine, dry, re-batch back into their original cases, and then seize one of three SPD staff for assembly. The corresponding assembly metrics are calculated globally and by weekday.



Section C-6 displays the autoclave and metric calculation section. Cases are cloned according to autoclave bath size, batch and seize of three autoclave machines, cool down after the autoclave, and then re-batch back to their original case. The case turnaround metric is then calculated globally and by weekday before the cases are disposed.

