REDUCING INPATIENT CONGESTION THROUGH SURGICAL SCHEDULING IN A MULTI-SITE NETWORK OF HOSPITALS: A CASE STUDY THAT APPLIES POOLING PRINCIPLES THROUGH MIXED INTEGER PROGRAMMING AND SIMULATION MODELLING

by

Adam Casey

Submitted in partial fulfilment of the requirements
for the degree of Masters of Applied Science

at

Dalhousie University
Halifax, Nova Scotia
October 2019

Table of Contents

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

Canadian hospitals experience downstream capacity resources, which reduces the total quality of care. The Master Surgical Schedule (MSS) is a primary driver of these downstream resources, including inpatients beds. This literature addresses this concern by utilizing a mathematical model to develop a MSS to minimize excess capacity in a series of nearby hospitals that share resources and governing bodies. The objective of this research is to develop a Mixed Integer Programming (MIP) model to generate MSSs in conjunction with a simulation model to quantify and illustrate the resulting changes. A two-step iterative approach was applied to the MIP and simulation where the historical inpatient LOS for each surgeon for the MIP is adjusted by adding the historical standard deviation multiplied by the ratio of excess capacity used in the simulation versus the MIP. A stopping criterion was established and the approach was followed until convergence, or a suboptimal loop was found.

The simulation model demonstrated statistically significant reductions using a student t-test for $\alpha=0.05$, up to 47% in total excess capacity using the MSSs developed by the MIP. The iterative approach did not initially converge using the initial adjustment formula, getting caught in a suboptimal loop. To overcome this, a range of predetermined adjustment factors was considered for the MIPs inpatient LOS data set to fully evaluate the solution set. By making these adjustments, the data sets were able to converge for (0.225, 0.25) standard deviations. The case study demonstrates the benefits of pooling principles for nearby hospitals, and provides a unique iterative approach to dealing with variability within a MIP model.

LIST OF ABBREVIATIONS

OR	Operating Room
MIP	Mixed Integer Program
PACU	Post-Anesthetic Care Unit
MSS	Master Surgical Schedule
LOS	Length of Stay
ELOS	Estimated Length of Stay
EH	Eastern Health
HSC	Health Science Center
SCM	St. Clare's Mercy Hospital
ENT	Ear Nose Throat
ALC	Alternative Level of Care
IP	Integer Program
ED	Emergency Department
OPT	Operating Time or Length of Operation
PICIS	PICIS OR System
DAD	Discharge Abstract Database

Chapter 1. Introduction

Canada’s healthcare demands and costs are rising with Canada’s aging population [1, 2]. Simultaneously, as healthcare demands have grown, Canadian’s expectations for their healthcare services have grown with it. Today Canadians expect shorter wait times and improved services [3].

The surgical scheduling problem has historically been a point of interest for healthcare providers, pursuing improvements for wait times, patient throughput, resource utilization and capacity constraints [4] [5]. Surgical scheduling is of significant interest because it is a key factor in determining the size of waitlists, hospital occupancy levels, and equipment processing. The surgeries performed in the operating room (OR) from the surgical schedule account for 70% of hospital admits and are a main determinant of many downstream hospital processes [6]. Producing an effective surgical schedule is a very complicated task. To produce a schedule many factors must be considered. Some factors are known and easy to determine, such as the availability of surgeons and equipment. Other factors, including the number of surgeries that will be performed in an OR block or how much time each patient will require in an inpatient ward are highly variable and difficult to predict [7]. When producing a surgical schedule it is important to not only consider patient throughput, but the effects on downstream resources such as inpatient wards. Improper planning of post procedural resources can have adverse effects including cancelled surgeries, inadequate care, patient delays and transfers.

Hospitals located in close proximity to one another provide an opportunity to potentially improve efficiencies by pooling their resources. Pooling resources has shown the ability to improve operational efficiencies and reduce costs [8] [9].

Pooling in healthcare examples include surgeons pooling their patient lists and the use of a central intake [10]. Comparing the effects of pooling between multiple hospitals is a relatively new research subject [11]. The objective of this thesis is to evaluate the efficiency of jointly developing surgical schedules between multiple sites in an attempt to reduce the variance and stress placed on inpatient wards.

The remainder of this thesis is broken into nine chapters. Chapter 2 introduces Eastern Health and background information relevant to the project. Chapters 3 and 4 present the problem and the purpose of this study. Chapter 5 reviews previous optimization techniques in healthcare as they relate to this thesis. The methods and formulations of the mixed integer program (MIP) and simulation models used are discussed in Chapter 6. In Chapters 7 and 8 the data analysis and results are discussed. Chapter 9 contains relevant discussions about the results and model limitations. Finally Chapter 10 summarizes the thesis and its findings.

Chapter 2. Background

This chapter examines the surgical process and how surgical schedules are developed. It provides an overview of the state of Canadian healthcare and its future direction. An overview of Eastern Health and the surgery department is also provided.

2.1 Surgical Process

When developing a surgical schedule it is important to understand patient flow throughout the operating department and hospital. Within most hospitals, patients follow a similar pattern. After the decision that surgery is required, but prior to their surgery, patients will be first booked on a waiting list and contacted when their operation date, time and location is known. Once the patient arrives at the facility, a hospital staff member will usually lead them through a series of laboratory tests, to ensure that it is safe to operate. The patient is then dressed for the operation. Once ready, the patient is transferred to the OR and placed on a table to be anesthetized and monitored. After the operation, the patient is transferred to the post-anaesthesia care unit (PACU) for further monitoring. Once the patient sufficiently recovers, they are moved to a bed in an inpatient ward or discharged [5] in the case of minor (day) surgery.

2.2 The Surgical Scheduling Problem

Surgical scheduling is the selecting and sequencing of surgical procedures within the designated time period [5]. The surgical scheduling problem is typically divided into three phases [4], [12]. The first phase is the case-mix planning, case-mix planning is the process of assigning how much OR time each surgical specialty will receive. The second phase is the development of the surgical schedule or the master surgical schedule (MSS).

Developing a MSS consists of identifying which specialty will use what operating rooms on what day. The final phase of the process is developing the patient mix. This phase is the assignment of patients and surgeons to an OR block with an operation date [4].

The MSS is a key component of a hospital's aggregate production plan [13]. It is a critical factor in determining pre-operative and post-operative resource requirements. A MSS assigns blocks of OR time to different surgical groups. Usually the MSS is constant from week to week for a period of time, but OR blocks may be split in half or have slight deviations between weeks to accommodate surgical groups that require less OR time. A sample MSS is presented in Figure 1. In this MSS there are 5 ORs each is used Monday through Friday. It is common practice for a MSS to designate both the surgeon's specialty and name as shown in rooms 1 and 2.

Room	Monday	Tuesday	Wednesday	Thursday	Friday
1	General Dr. Smith	General	Plastics Dr. A Smith	Vascular Dr. Black	ENT Rotating
2	Vascular Dr. Brown	Vascular Dr. Black	General Dr. Smith	Vascular Dr. Brown	General Dr. Walker
3	Urology	Urology	Urology	Urology	Urology
4	Cardiovascular	Cardiovascular	Cardiovascular	Cardiovascular	Ent/Dentals General Dr. Casey
5	ENT	General	ENT	ENT	Thoracics

Figure 1 A Master Surgical Schedule

The process of developing a MSS is complex task because of the numerous objectives, stakeholders and resources involved [14]. A MSS must determine how much time to allocate to each specialty and what the demands are on the pre and post-operative resources. Variance is inherent in the scheduling problem. Emergency cases and uncertainty surrounding the exact nature of the required procedures for a given patient contribute to this variance [5]. A good surgical schedule needs to balance both the needs of surgeons and hospital resources. It should be consistent week to week and respect the bounds and constraints of the hospital [4]. Developing a MSS has many considerations including:

1. The Operating Room's capabilities- An OR's capabilities are used to determine if a surgery can be scheduled in a block. The OR needs to have the necessary equipment required for the surgery.
2. The number of available beds- The number of available beds is a determinant of the number of surgeries that can be performed in an OR block. After the operation, there needs to be a place for the patient to go. If there are no available beds, that patient is forced to remain in a recovery area, which is not generally designed to hold patients for extended periods.
3. The number of operations a physician will perform in an OR block- Historical data is often used to predict how many operations a surgeon will perform in an OR block.
4. The Length of stay (LOS) for a given physician and surgery type - Historical data is often used to predict how long a patient will stay in hospital after a specific surgery type.

2.3 The State of Canada's Healthcare

Wait times and the state of Canadian healthcare continues to be a concern of Canadians. Waitlists continue to grow and at the same time Canadian's expectations for healthcare demands continue to increase. Addressing the increasing size of waitlists is a priority of the Canadian government. Provincial and territorial healthcare systems have begun actively monitoring patient wait times, making the data publically available. Provincial governments continue to develop policies and strategies to address these issues. These plans and policies often are based on research directly tied to surgical resources and Master Surgical Schedules (MSSs).

To reduce wait times, hospitals must service patients faster to reduce the quantity of patients on its waitlist. Patients are removed upon completion of their surgery or if their assessment changes and they no longer require the operation. A by-product of pushing wait list improvements is more patients in hospitals and higher utilization of hospital resources**.** If poorly managed higher utilization rates lead to capacity issues and a lower level of care. The focal point of this thesis is addressing the MSS to account for patient demand to reduce congestion within a multi-hospital network.

2.4 Eastern Health

Eastern Health (EH) is Newfoundland's largest health board extending from St. John's to Port Blandford and includes all communities within the Avalon, Burin and Bonavista Peninsulas. Eastern Health's span of coverage is shown in Figure 2.

Figure 2 Eastern Health's Territory

EH serves a population of over 300,000, comprised of over 13,000 employees and 5 hospitals:

1. Health Science Center (HSC)
2. St. Clare's Mercy Hospital (SCM)
3. Carbonear General Hospital
4. Dr. G. B. Cross Memorial Hospital
5. Burin Peninsula Healthcare Center

Beyond its main population, EH is also the tertiary healthcare provider for all of Newfoundland. The majority of EH's surgical operations occur within its two city hospitals: SCM and The Health Science Center HSC. HSC is an academic hospital and is Newfoundland's primary tertiary hospital. HSC has 45 OR blocks and 103 designated surgery beds. SCM is the older of the two hospitals, having 35 OR blocks and 113 designated surgery beds. The two hospitals are located within close proximity and have an existing relationship where certain surgical staff and equipment are shared between the two sites. In 2013 Easter Health was recognized for its Orthopedic Central Intake, which greatly reduced patient wait times and demonstrated its commitment to realizing the benefits of pooling resources.

The research of this thesis examines HSC and SCM as a network of hospitals. The other hospitals within Eastern Health were excluded from this network because their geographic locations do not allow for easy resource sharing. As mentioned earlier, pooling resources like surgeons and surgical equipment increases complexity, but it also provides opportunities for improved efficiencies [8].

When developing surgical schedules for a network of hospitals, it is important to consider the current state and how easily transferring services will be. Within this small hospital network, some level of resource sharing already exists. The two hospitals share laundry facilities and a common medical device reprocessing area. Beyond these, there are three groups of surgical specialties, orthopaedics, general and plastic surgery that are commonly performed at both sites.

At the two hospitals there are 10 physicians that operate each week at both sites and 18 physicians that perform surgeries within one of the three shared groups of surgical specialties. Moving other surgical groups between the two sites is possible, but it would incur a high cost. The process would require a large initial investment to modify the OR and purchase new equipment or incur the costs of frequently transporting expensive devices between the two sites.

The focus of this project is to optimize the MSS to level the bed capacity between sites and inpatient wards. A key objective is minimizing the amount of overcapacity bed days used. For the purpose of this research, an overcapacity bed is defined as anything serving as a bed that is not included in the hospital's main bed board.

There are two other projects ongoing that may affect the results of this project. A Real Time Demand Capacity initiative is focused on improving the discharge process for nurses in the hospital wards. This project's goal is to discharge patients earlier in the day, by proactively managing their discharge requirements. If successful, this project will free up ward resources including beds and nurses earlier in the day. It is important to free up hospital beds as efficiently as possible to have them ready for the new batch of patients that will require them post-surgery. Freeing up beds will allow new patients from the OR to be transferred into the wards. The second project that could affect the results is a Clinical Utilization Review. This review is examining each of the physician's usage of their OR time. The Clinical Utilization Review is considering elimination of half OR blocks. The results of the review will lead to changes in the amount of OR time assigned to each physician and specialty. Changes to the amount of OR time designated to each surgical specialty will alter the designation of blocks within the MSS.

2.5 Surgery Department Description

This section will describe the surgery departments at the HSC and SCM hospitals. It will describe the types of surgeries that are performed and patients that are seen, and how patients flow throughout. It will describe how patients are classified and the resources that they use.

2.5.1 Patient Types

This research includes both elective and non-elective patients from all surgical groups at the HSC and SCM hospitals. Between the two sites there are 12 primary surgical groups that use the ORs:

1. Cardiovascular Surgery
2. Dental/ Oral Surgery
3. General Surgery
4. Gynecology
5. Ear Nose and Throat (ENT)
6. Neurosurgery
7. Ophthalmology
8. Orthopaedic Surgery
9. Plastic Surgery
10. Thoracic Surgery
11. Urology
12. Vascular Surgery

Some cancer treatment is also scheduled within the surgical ORs. Only general surgery, orthopaedic surgery and plastic surgery are performed at both sites. Surgery types performed at both site is a significant optimization constraint, EH has specified that they do not have the budget at this time to adjust the hospitals to accommodate a new surgical group. This limits the potential shifting of surgeons to surgeons that perform one of the above mentioned surgeries.

2.5.2 Patient Flow

All surgery types follow the same general flow. The patient is selected from the surgeon's wait list and enters the hospital that the surgeon is operating in, on that day. The patient waits until the required surgeon and equipment are ready before entering the operating room for pre-surgery care. Once the patient is prepped the operation begins. Following the operation patients can be either discharged (outpatients) or admitted (inpatients). Admitted patients will occupy a bed resource for their entire LOS. Non-elective emergency patients enter the stream from referrals from the ED or another hospital service. Their arrivals are less predictable. Once they enter the operating room they follow the same procedure as elective patients. Occasionally non-surgery patients will enter and use surgical resources, usually because they do not have enough resources within their department. Figure 3 demonstrates the flow of surgery patients through surgical resources. Within Figure 3, the green line represents emergency cases that resulted in surgery and the purple dashed line between the two hospitals inpatient wards represents transferring of patients between sites. Transfers are done either because one hospital currently does not have the required resources or the patient requires treatments that can only be provided at the other site or in anticipation of future demand to balance the demands between sites.

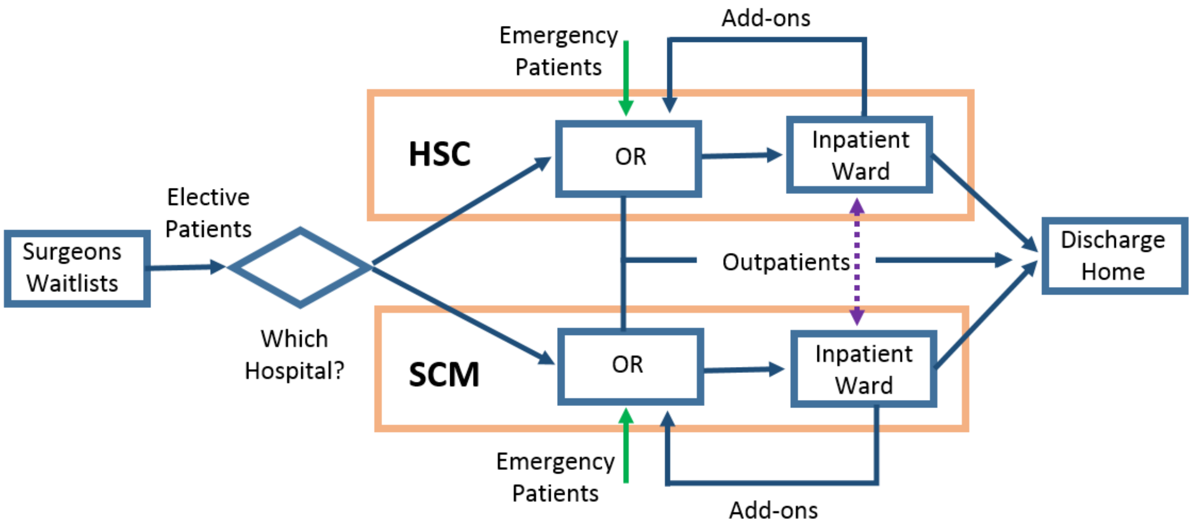

Figure 3 Patient Flow through Surgical Resources

2.5.3 Facilities and Resources

Surgeons determine which patients to operate on based on how long they have been on the waitlist and the urgency of their case. Once a patient enters the hospital they will require an OR and the surgeon during their procedure. Following the procedure patients will typically use a PACU until they are ready to be discharged or admitted. Admitted patients will use designated surgery beds in an inpatient ward as well as members of the nursing staff to assist in their care.

2.5.4 Diagnosis Classification

Prior to surgery, patients are assigned a diagnosis. The surgeon and hospital staff use this diagnosis and information about the patient’s overall health to estimate their required operating room time (OPT) and LOS. The patients are broken down by their case procedure (i.e. general surgery) and then further by their case mix group. Between 2012 and 2015 there were over 790 different case mixes assigned to patients.

Chapter 3. Problem Statement

Eastern Health's HSC frequently experiences capacity issues. These issues have resulted in short-term solutions, which often have adverse effects including: patients residing in hallways, patients residing in the PACU for lengthy periods of time, patients being transferred to other sites, surgery cancellations, overtime and frustration for those involved. One of EH's identified problems is that on average patients LOS exceeds their estimated LOS (ELOS) by 14%. Longer LOS increase the total bed day used and heighten capacity issues. Through interviews with managers and key stakeholders, including Eastern Health's COO, the surgical chiefs for HSC and SCM, the regional director for clinical efficiency and the process improvement manager several theories for the higher LOS were identified:

1. Incorrectly categorizing patients prior to their surgery
2. Inefficiently discharging patients, not clearing bed resource in time for new patients
3. Alternative Level of Care (ALC) patients occupying surgery resources
4. Non-surgery patients occupying surgery resources
5. The MSS

To better understand the problem, historical bed usage was examined at both of the sites. The daily results between 2011 and 2012 were mapped against the number of available beds in Figure 4 and Figure 5. The chart shows the total quantity of bed days for each day as the sum of cumulative bed days excluding July and August for elective patients,

patients that have been diagnosed as alternative level of care (ALCDays) and patients from other departments (OffServiceDays).

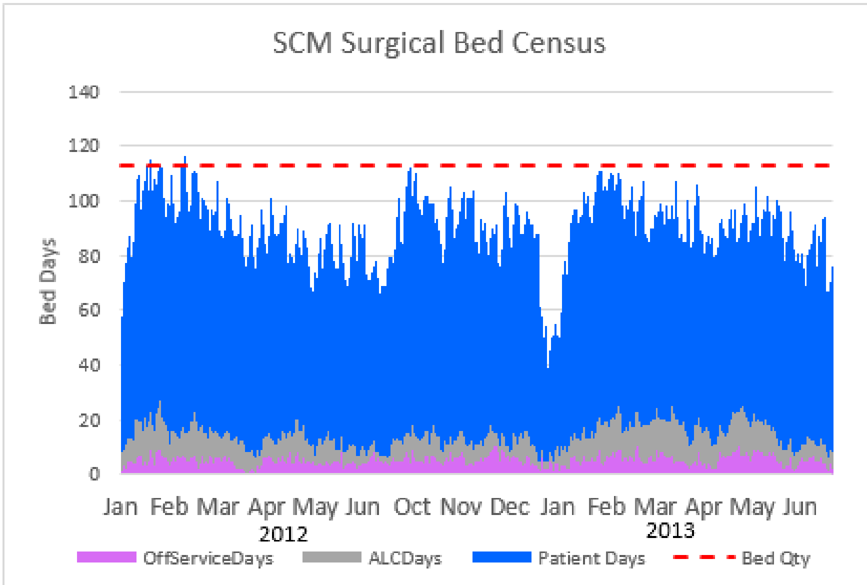

Figure 4 SCM Surgical Bed Usage

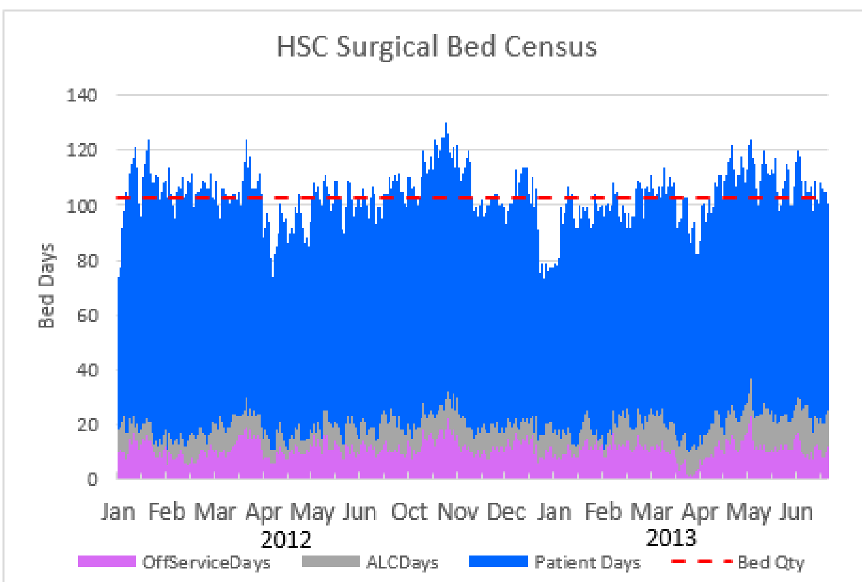

Figure 5 HSC Surgical Bed Usage

Figures 4 and 5 indicate that there is significantly more capacity at SCM than HSC which is regularly above its bed capacity and during busy periods by a significant amount. In fact surgical bed usage at HSC is at capacity on 83.4% of the sampled days, compared to just 2.1% at SCM. Bed distribution by the day of the week can also be used as an indicator of how hospitals are managing their capacity. Figure 6 and Figure 7 plot the average quantity of surgery patients in surgical beds by day of week (Bed Days).

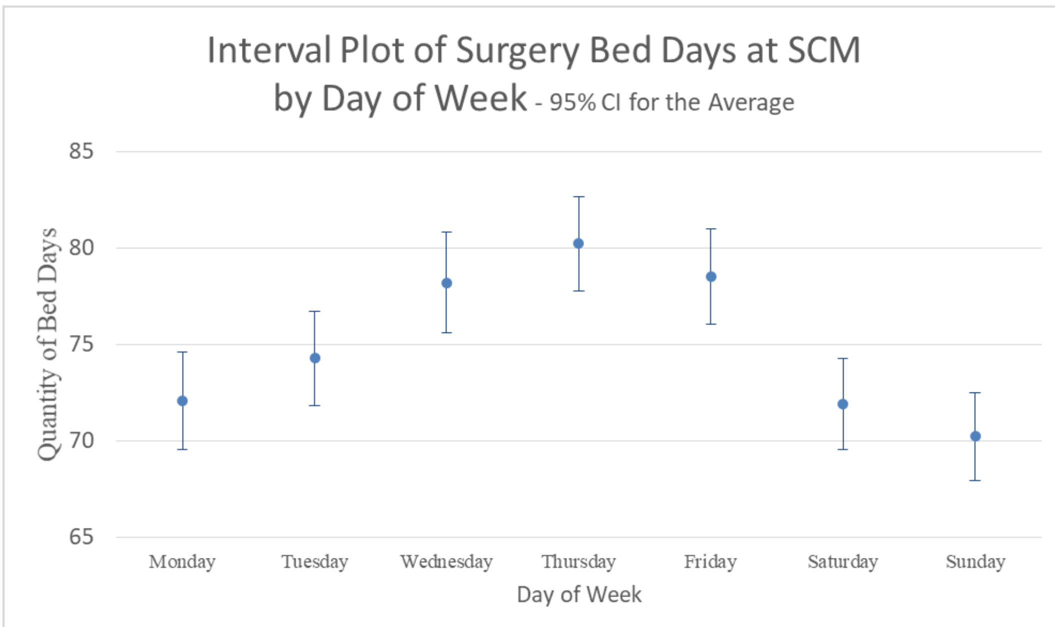

Figure 6 Surgery Patient Daily Bed Days SCM

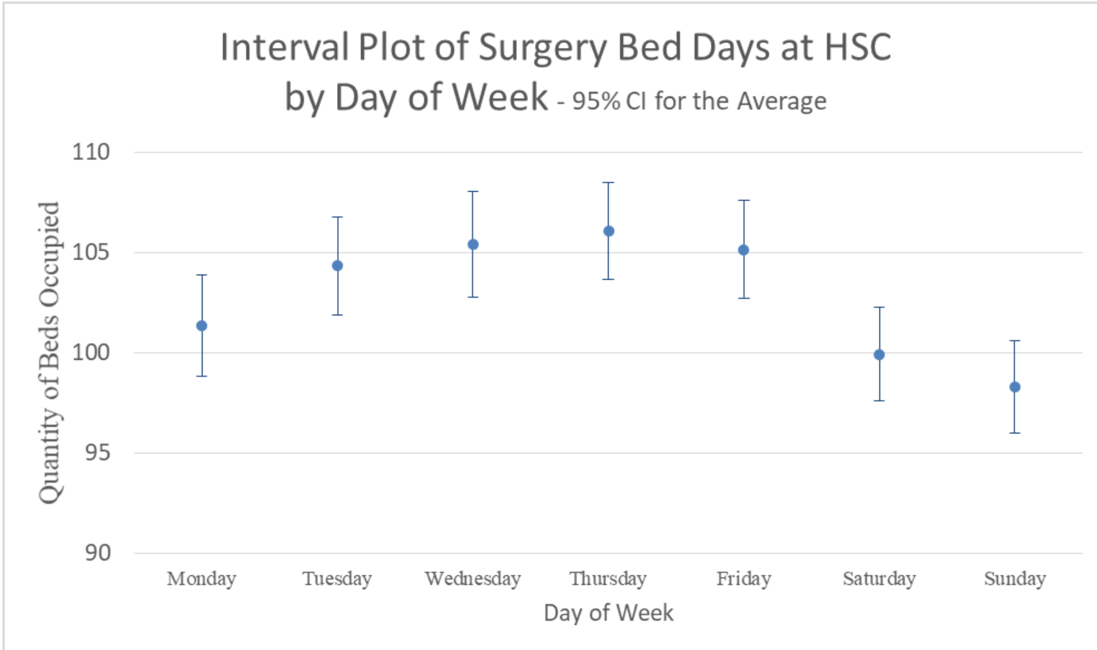

Figure 7 Surgery Patients Daily HSC

Both data sets have an upward trend towards Thursday and Friday; although there is no significant differences at HSC between Tuesday and Friday. Intuitively this makes sense, elective surgeries are completed on weekdays which typically results in a net gain of inpatients. Weekends typically result in a net loss of inpatients because, without scheduled elective surgeries, there are more discharges than admissions. Examining the data, it is clear that there is more variability between the days in the quantity of patients at the SCM compared to HSC. One hypothesis for this proposed by management is that HSC has less variability because it is more often at maximum capacity. When HSC is at maximum capacity, it is forced to transfer patients or cancel surgeries, which keeps the bed utilization more stable, near its maximum capacity throughout the week.

The combination of surplus bed capacity at SCM and the imbalance of bed utilization throughout the week indicate that potential improvements in balancing bed demand could be achieved by pooling the resources and redesigning the MSSs for the two sites. To highlight some of the potential gains, Figure 8 illustrates the total combined surgical bed usage for HSC and SCM.

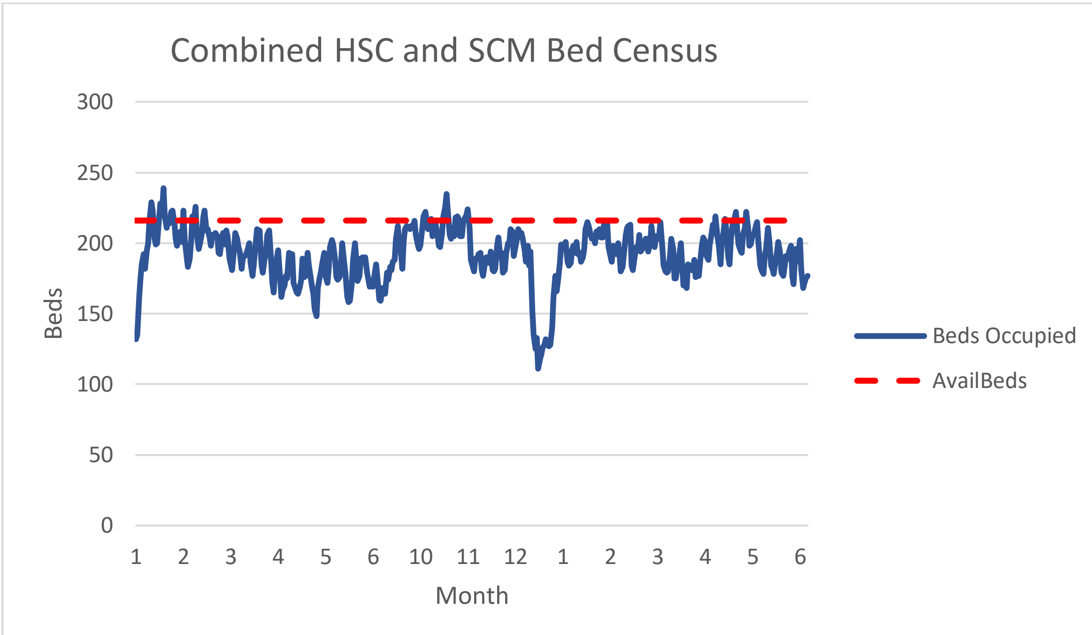

Figure 8 Combined Bed Usage

The historical data is summarized in Table 1, displaying the average, and quartile data. Together Figure 8 and Table 1 indicate that significant improvements could be made if the hospitals were able to pool perfectly.

	HSC	SCM	Combined	Beds Available
Average	103.0	89.2	192.1	216
1^{st} Quartile	98	83	181	216
Med	103	91	194	216
3^{rd} Quartile	109	97	206	216
Max	130	116	246	216

Table 1Historical Bed Statistics

Chapter 4. Purpose of Study

Based on historical data it is possible to estimate the number of patients, the type of patients and patient's lengths of stay that will enter the hospital from a surgeon utilizing an OR block. Using these estimates it is possible to influence MSSs and reduce problems related to inpatient congestion. The purpose of this paper is to demonstrate whether a two-step iterative approach using both a MIP and simulation can be used to approximate an optimal solution to better level bed capacity between a series of nearby hospitals. The mathematical model will be used to develop solutions sets and the simulation model to validate and quantify any improvements.

Chapter 5. Literature Review

Appointment planning and scheduling in healthcare has widely been studied. Gupta and Denton provide an in-depth review of current research and opportunities [14]. This thesis builds on the literature on the benefits of pooling resources and literature on surgical scheduling to minimize capacity constraints. This approach of pooling hospitals and using mathematical modelling to optimize their joint function is relatively new. The following chapter will discuss related literature.

Since its initial application to healthcare, Operations Research techniques have become a critical component in the efficient delivery of healthcare services [15]. These techniques target improvement measures and cost reductions. Citizens have high expectations for the delivery of their healthcare services. These high expectations strain healthcare's resources. To keep up with these demands and not exceed their budget; healthcare providers depend on Operations research techniques, including integer programming (IP) methods. IP techniques have been applied commonly across many healthcare sectors including optimal appointment scheduling [14], the delivery of homecare, surge capacity planning, and the focus of this paper, surgical scheduling [15].

Historically, the assignment of surgical specialties was developed by an administrator who had to consider all of the vast objectives. Recently, operations research techniques have been applied to the surgical scheduling problem with improved results. In the literature, the majority of research has focused on maximizing operations research utilization or similar functions such as minimizing staffing costs and reducing uncertainty [16], [17], [18], [19]. A body of research is dedicated towards a two-step approach to optimization. This research generally uses a MIP model to find solutions and simulation models to predict what implications the solution has and to perform a sensitivity analysis [20]. One such study uses a simulation model coupled with a TABU search method to optimize the MSS. It was too computationally expensive to optimize using only a simulation model, so (Qing et al) applied a TABU search to reduce computing time and generate a good approximation [21]. Blake and Carter [4] developed a MIP and further heuristics at Mt. Sinai Hospital to assist administration staff in modify their MSS to account for changes in funding total OR time.

A growing body of research is being developed for leveling bed capacity and managing post-operative resources [22]. VanBerkel et al. [7] improved the levelness of bed ward capacity through a combination of an operations research model and input from knowledgeable physicians and stakeholders. A two-phase model was developed that saw improvements to ward congestion. This system consisted of a Surgical Schedule Organization and an IP model designed to reduce surgical ward capacity. The results of the IP model were then tested in a bed utilization simulator, an implementation of a Monte Carlo simulation [23].

At the time of this writing, only [24] has been identified in literature as considering bed smoothing across a network of hospitals. Bed smoothing involves leveling the amount of bed usage across the different hospitals, so that demand is balanced. The Fraser Health Authority uses an IP to determine the optimal MSS across regions of hospitals, grouping hospitals together that are in close proximity. In their model, resources like surgeons and surgical equipment are shared between the hospitals. Their research showed that by pooling resources, Fraser Health was able to reduce bed congestion. EH has already seen some benefits of pooling resources with the implementation of a central intake for hip and knee surgery assessments [25]**.** Future research will be able to build on the research performed at the Fraser Health Authority. Belien and Demeulemeester [22] developed several MIP models to level bed capacity. Several of their models accounted for variance and uncertainty in a surgeon's patient mix and patient LOS. Although they do not account for a system of hospitals, its concepts for considering variance can be applied to further research.

Chapter 6. Methodology

Chapter 2 identifies the close proximity of Eastern Health's HSC and SCM hospitals as a natural research opportunity to study the unique effects of pooling resources between two hospital sites. The goal of this research is to alleviate capacity problems experienced at HSC through balancing the bed demand. This research intends to accomplish this goal by optimizing the two hospitals MSSs to minimize capacity issues. The solution space is explored using a two-step iterative method that consists of a MIP and a simulation model. The MIP uses a mathematical formulation to optimize the MSSs to minimize variation in resource utilization. The outputted MSSs are then inputted into the simulation model to reaffirm the MIP models results and better quantify improvements. The bed statistics are compared between the simulation and MIP models. The results from the simulation model are used to adjust an adjustment factor for patient LOS within the MIP. This process is repeated until the results converge (no statistical difference for $\alpha = 0.05$). An alternative method that could have used is the Sample Average Approximation (SAA) method, which could have utilized the same stopping criteria. This chapter will describe the iterative process used to optimize the MSSs as well as the methods used in developing the MIP and the simulation model.

6.1 Iterative Process

Solutions based solely on historical averages risk not providing the right solution to fit demand when the underlying system is highly variable. This research uses a two-step iterative approach to take variability into account. Specifically, the LOS parameters in the MIP are increased by a fraction of the standard deviation. The first step in this approach is the MIP (described in Section 6.2); in the MIP the historical LOS averages and standard deviations for each surgeon are used to determine the MIP LOS. The historical LOS standard deviations are multiplied by an adjustment Factor F to increase the historical average LOS for each surgeon as shown in Equation 1. This adjustment is done to synchronize the results between the MIP and simulation. F is initially arbitrarily selected and then adjusted by Equation 2 as additional simulations are run. The MIP then explores the solution set using the resulting LOS and historical average quantity of daily operations to minimize the quantity of overcapacity bed days to produce new MSSs.

[1] $LOS_S = \mu LOS_S + F^{*}\sigma LOS_S$ for each surgeon S

The second step (described in Section 6.3) is a simulation, which produces more descriptive bed statistics. The simulation is run using the MSSs generated by the MIP in step 1. In the initial iteration, the adjustment factor is arbitrarily chosen, after subsequent iterations the adjustment factor is refined by the ratio of overcapacity bed days from the simulation divided by the overcapacity bed days from the MIP (as shown in Equation 2). After completing the simulation run and comparing the bed statistics, F is used to adjust the LOS for each surgeon in the MIP and the MIP rerun with the new parameters to generate new MSSs to be used in the simulation model. This process is repeated until the difference in overcapacity bed days converges and is statistically insignificant for $\alpha = 0.05$. The general algorithm process is described in detail below:

Step 1. Start
Step 2. Arbitrarily select adjustment factor F
Step 3. Run the MIP model, generate MSSs and determine the total number of overcapacity bed days

Step 4. Run the simulation model using the MSSs from the MIP and determine the total number of overcapacity bed days

Step 5. Check if the difference between the two sets of results are statistically significant for $\alpha = 0.05$?

If No then

Exit and record results

Else

Adjust adjustment factor

[2] $F_i = F_{i-1} * \frac{Overcapacity\ Bed\ Days\ Simulation}{Overcapacity\ Bed\ Days\ MIP}$ for each $i > 1$.

And return to step 2.

Step 6. Finish

Figure 9 illustrates the flow chart for the general algorithm.

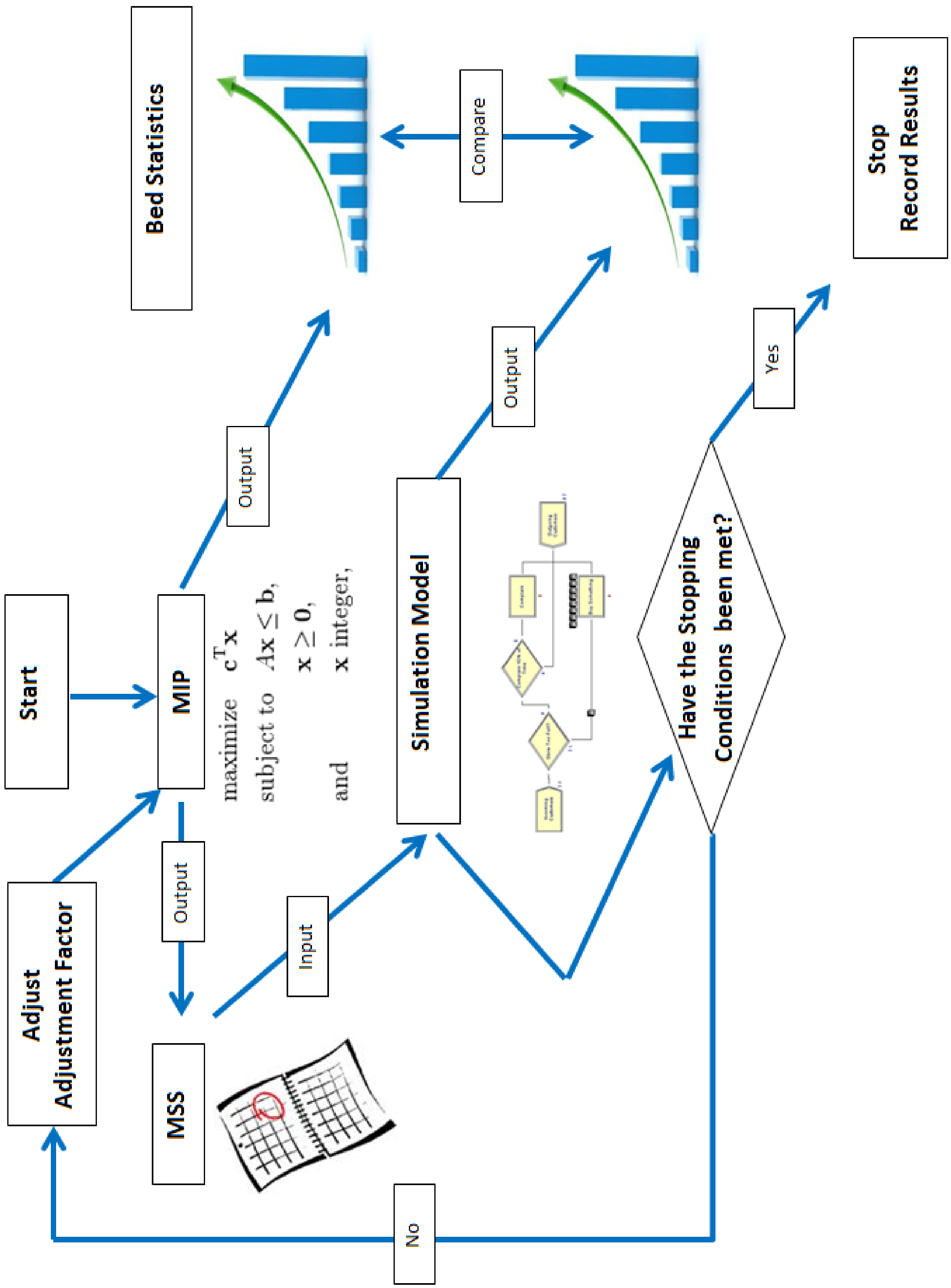

Figure 9 Two-Phase Approach Algorithm

6.2 Mixed Integer Program

This project develops a MIP to generate MSSs for a set of hospitals. The goal of the MIP is to generate a set of MSSs that minimize capacity issues experienced within HSC and SCM. The formulation considers the hospitals as a network of hospitals. Jointly considering the two hospitals allows the MIP to take advantage of gains from pooling resources to level the daily and overall demand occupancy. The following subsections will discuss the model requirements, design and its formulation.

6.2.1 Model Requirements

Working closely with key stakeholders, including Eastern Health's COO, the surgical chief for HSC and SCM, the regional director for clinical efficiency and the process improvement manager it was determined that the MIP should focus on the second phase of surgical scheduling, designating surgeons and specialties to OR blocks, with the goal to balance bed demands. The MIP needed to address the congestion problems experienced at HSC and attempt to improve the uneven bed demand between sites and throughout the week. To accomplish this, the MIP needed to first accurately model the current situation. The MIP uses historical data to determine the patient mix and LOS for each surgeon. It has been shown that deterministic models using historical averages does not guarantee an optimal solution and underestimate capacity issues [20]. Acknowledging this underestimate, a multiple of the standard deviation was added to the average patient LOS for each surgeon. An adjustment factor linearly revises the standard deviation multiple after each iteration in an attempt to pair the MIP and simulations results. The function was applied to each surgeon separately to produce more realistic results. For example, it would not be representative to increase the average patient LOS for a surgeon who performed only day surgeries by the same amount as a physician that performed complex surgeries with varying recovery times. Results from the MIP include a daily bed census and MSSs for both HSC and SCM. The outputted MSSs identify the operating specialty and surgeon for each OR block. Management at EH required the MIP to maintain current surgical volumes and OR relationships for each surgical specialty and surgeon. This means that a surgeon cannot be assigned less OR time than they currently have and they cannot operate in operating rooms not equipped for their specialty. The MIP also attempts to incorporate changes requested by EH staff. Requests included eliminating days where a surgeon operates a partial block at each site and where possible eliminating partial block assignments entirely.

6.2.2 Mixed Integer Programming Model Description

A mathematical formulation was used to evaluate a solution set of MSSs and determine the bed usage at HSC and SCM using constant values for surgeon operations and patient LOS based on surgeons historical data for LOS and quantity of daily operations. The objective function is to minimize the number of overcapacity bed days. The model considers any bed in excess of the typical ward layout (113 and 103 at SCM and HSC respectively) to be an overcapacity bed. Each hospital is equipped with a set number of physical beds in their inpatient wards but has designated overcapacity beds and overflow areas to accommodate additional demand. To minimize the number of overcapacity beds, the formulation manipulates the MSS to find an optimal configuration of assigned surgeons to ORs. Constraints are used to control the operating rooms that surgeons can operate in and ensure that each surgeon receives their minimum OR time. This section will describe the methods that were used in developing the formulation.

The model consists of two hospitals and 72 surgeons. At HSC and SCM there are only 65 surgeons, but an additional 7 surgeons were created to schedule oddities. For the purpose of this paper an oddity is considered to be an OR block not assigned to a specific surgeon. For instance if an OR block was designated to an entire specialty such as General Surgery (a rotation of general surgeons) then a surgeon was created for the model using cumulative historical data from all surgeons that operate in that OR block. The MIP uses a two week planning horizon instead. Expanding the planning horizon to two weeks from one allows the model to assign rotating blocks instead of partial blocks to surgeons. For instance, instead of surgeon A operating in the morning and surgeon B in the afternoon, surgeon A would operate every odd week and surgeon B every even week. The model's objective is to minimize the sum of each hospital's demand above its set capacity computed over a 36 week period. The 36 week period was selected to represent the regular schedule used by the two sites. Both hospitals use three schedules throughout the year: a regular schedule (36 weeks), a summer schedule (14 weeks) and a Christmas schedule (2 weeks) over the holiday break.

The MIP was developed using GLPK within Gusek and then Gurobi was used to read and optimize the MIP. The model sets the current amount of operating time and OR blocks assigned to each surgeon as a constraint. This limits the model to schedules that move surgeons OR blocks, but does not affect their allotted OR time. The MIP repeats the same schedule, patient mix and patient LOS every two weeks. The historical patient mix and average LOS underestimate the demand and represents an idealistic scenario. An adjustment factor F (described in Section 6.1) is used to better reflect reality and synchronize the MIP results with the simulation results. After each iteration the ratio of bed usage between the simulation and MIP is used to adjust F. For example if the simulation model had 100 overcapacity bed days and the

MIP had 90 overcapacity bed days then F would be increased by 10/9. This process is repeated after each iteration until the difference between the two models is no longer statistically significant for $\alpha = 0.05$.

6.2.2.1 Mixed Integer Programming Model Formulation

The model breaks down critical components by sets. These sets are used to define variables, parameters and constraints. The formulation is comprised of 6 sets:

1. D is the set of days indexed by d.
2. P is the set of physicians indexed by p
3. H is the set of hospitals indexed by h
4. O is the set of operating rooms indexed by o. Where $O = \{O_1 \cup O_2\}$
    i. O_1 is the set of operating rooms in hospital 1
    ii. O_2 is the set of operating rooms in hospital 2
5. B is the set of operating room blocks indexed by b
6. I is the set of beds indexed by i

Using days as the MIP model's time period restricts the addition and removal of patients to the start of each day.

The model uses parameters to input values into the models constraints. For instance a parameter (Surgeon Site) is used to designate whether physician p can operate in hospital h. If the physician can operate at the site the parameter is designated a value of 1, if they cannot operate at that site the parameter is assigned a value of 0. The model consists of seven parameters:

1. SB_p is the number of OR blocks assigned to surgeon p
2. SH_{ph} is binary 1 if surgeon p can operate at hospital h, 0 otherwise
3. SO_{po} is binary 1 if physician p can operating in OR o, 0 otherwise

4. NP_p is the expected number of patients that will be admitted when surgeon p is assigned an OR block
5. LOS_p is the expected length of stay for patients operated on by surgeon p
6. $LOSD_p$ is the LOS standard deviation for patients operated on by surgeon p
7. $LOSAdj_p$ is the adjusted LOS for physician p accounting for the surgeon's variance using the adjustment factor F, which relates the bed statistics between the simulation and MIP. It is determined by the following equation:

$$LOSAdj_p = LOS_p + F * \mathrm{LOSDp}$$

Where F is determined by the relationship between the bed statistics of the simulation and the MIP as described in Section 6.1

8. BED_h is the number of beds assigned to each hospital h.

The model decision variable is:

$$x_{pdo} \begin{cases} 1 \ if\ surgeon\ p\ operates\ on\ day\ d\ in\ operating\ room\ o \\ 0\ Otherwise \end{cases}$$

$\forall p \in P, \forall d \in D, \forall o \in O$

The other model variables include:

$$PH_{dh}\ is\ the\ number\ of\ patients\ to\ send\ home\ on\ day\ d\ from\ hospital\ h$$

$\forall d \in D, \forall h \in H, >= 0$, integer

$$PA_{dh}\ is\ the\ number\ of\ patients\ to\ admit\ on\ day\ d\ from\ hospital\ h$$

$\forall d \in D, \forall h \in H, >= 0$, integer

$$OB_{dh}\ is\ the\ number\ of\ beds\ occupied\ on\ day\ d\ in\ hospital\ h$$

$\forall d \in D, \forall h \in H, >= 0$, integer

$$OFB_{dh}\ is\ the\ number\ of\ overflow\ beds\ occupied\ on\ day\ d\ in\ hospital\ h$$

$\forall d \in D, \forall h \in H, >= 0$, integer

Overflow beds are used to track the number of extra beds used. The model does not place a maximum on the number of overflow beds. By not placing a maximum does not need to cancel surgeries and can better quantify how much extra demand there actually is. There is no maximum placed on this variable, therefore it captures the entire excess demand and surgeries are not cancelled.

Using these variables and parameters the model can be stated formally as follows:

Objective:

$$minimize\ obj: \sum_{d}^{D} \sum_{h}^{H} OFB_{dh}$$

Subject to

[1]$\sum_{p}^{P} \sum_{o}^{O} x_{pdo} = 0, \quad \forall \mathrm{d} \in 6..7, \forall \mathrm{d} \in 13..14$ No Saturday or Sundays

[2]$x_{pdo} \leq SH_{p1} \quad \forall \mathrm{p} \in \mathrm{P}, \forall \mathrm{d} \in \mathrm{D}, \forall \mathrm{o} \in O_1 \}$ Do not assign surgeon to hospital they cannot operate at

[3]$x_{pdo} \leq SH_{p2} \quad \forall \mathrm{p} \in \mathrm{P}, \forall \mathrm{d} \in \mathrm{D}, \forall \mathrm{o} \in O_2 \}$ Do not assign surgeon to hospital they cannot operate at

[3]$x_{pdo} \leq SO_{p1} \quad \forall \mathrm{p} \in \mathrm{P}, \forall \mathrm{d} \in \mathrm{D}, \forall \mathrm{o} \in O_1 \}$ Do not assign surgeon to an OR in OR set 1 that is not properly equipped

[3]$x_{pdo} \leq SO_{p2}$ $\forall$ p $\in$ P, $\forall$ d $\in$ D, $\forall$ o $\in$ O_2 } Do not assign surgeon to an OR in OR set 2 that is not properly equipped

[4] $\sum_d^D \sum_o^O x_{pdo} \geq SB_p$ $\forall$ p $\in$ P Every surgeon gets at least SB_p slots

[5]$PA_{d1} = \sum_o^{O1} \sum_d^D x_{pdo} * NP_p$ $\forall$ d $\in$ D Patients added to hospital 1 each day

[6]$PA_{d2} = \sum_o^{O2} \sum_d^D x_{pdo} * NP_p$ $\forall$ d $\in$ D Patients added to hospital 2 each day

[7]$PH_{d1} = \sum_p^P \sum_o^{O1} \sum_{d1}^D x_{pdo} * NP_p$ $\forall$ d $\in$ D $\cap$ 1 Discharges at hospital 1 each day

[8]$PH_{d2} = \sum_p^P \sum_o^{O2} \sum_{d1}^D x_{pdo} * NP_p$ $\forall$ d $\in$ D $\cap$ 1 Discharges at hospital 2 each day

[9]$OB_{dh} = OB_{d-1,h} + PA_{dh} - PH_{dh}$ $\forall$ d $\in$ 2..D, h $\in$ H

Bed Census

[10]$OB_{dh} \leq Beds_h + OFB_{dh}$ $\forall$ d $\in$ 2..14, h $\in$ H Cannot exceed quantity of overflow beds

[11]$x_{pdo} = x_{pd-14,o}$ $\forall$ p $\in$ P, $\forall$ d $\in$ 15..129, o $\in$ O Surgical schedule repeats every two weeks.

[12] $\sum_p^P x_{pdo} \leq 1$ $\forall$ d $\in$ D, $\forall$ o $\in$ O Only 1 physician can operate per day per OR block

[13] $\sum_o^O x_{pdo} \leq 1$ $\forall$ p $\in$ P, $\forall$ d $\in$ D Only 1 hospital can be operated per day per surgeon

Constraint 11 defines the length of the MSS in the model. In this case the MSS is set to two weeks repeating schedule.

6.3 Simulation

The complexity and variance in resource availability, patient mixes and patient LOS makes it difficult to apply queuing theory to surgical scheduling and OR planning. In place of queuing theory, surgical scheduling problems often utilize computer simulations as a planning aid [26]. This paper takes an iterative approach to this problem using both a MIP and a simulation model. Mathematical formulations are great tools to optimize complex problems, but are limited in their ability to use distributions and variance of patient mixes, LOS and operation lengths. Simulation models allow users to fit historical data into distributions and use the distributions to determine the mix of patients, their operating times and their LOS. Simulations can be easily visualized and broken into small components, which allows the modeller to dissect each component and validate that it works as intended. The main objective of the simulation model in this research is quantifying the effects of changes made to the MSSs and providing feedback to the MIP. The following subsections will discuss the model requirements, design. They will also describe the model, its resources, entities and flow of patients.

6.3.1 Simulation Requirements

The simulation model provides an inexpensive opportunity to detect potential problems caused by a new MSS before system changes are implemented. As such the model must be accurate and repeatable. To ensure its accuracy and effectiveness the model must be validated and verified through system checks and comparing results to historical outputs. For this paper repeatability means that the model is able to apply the same data set independent of the MSS. Finally the model needs to be relevant. In order for successful change management to occur the organization has to believe in the concepts and the importance of the solutions.

6.3.2 Simulation Design

The conceptual model was formulated through a process review with key staff members familiar with the process including the surgical chief for SCM and HSC and the regional director for clinical efficiency and the nursing staff, and examining previous literature. The model was developed using Rockwell's Arena software and utilizes historical data from Eastern Health's databases. The entire surgical process and its many complexities were considered during development. The model was set-up to evaluate and compare the effects of changes made to the MSSs. The model was validated by a series of tests and statistical analysis. This models process was verified through quantitative analysis and a review with people with an understanding of patient flow throughout EH's surgery departments.

The simulation was designed to capture all patients that utilize surgical resources. The simulation captures two patient streams, elective and non-elective patients. Elective patients arrive in the system on the day they are scheduled for surgery as sourced by the MSS. Non-elective patients typically enter the system through the Emergency Department (ED) when the ED doctor requests consultation that results in surgery. The model captures the flow of the patients from their arrival until they are discharged.

6.3.3 Simulation Model Description

The model uses a database to determine model inputs and process times. These inputs include the MSS, patient LOS in days and operation length in minutes. The model utilizes four phases to model patient flow. Phase one initializes the model inputs key parameters from the database. This phase assigns a patient list to each physician, where each patient is assigned attributes (i.e. operation time and LOS) based on the physician's historical patient mix. Phase two models the arrival of patients into the hospital. Emergency patients arrive randomly according to historical arrival rates. For the purpose of this model, arrivals are based on when a patient is selected for surgery and prepared for the OR. Elective patient arrivals are determined from the MSS and a function that selects patients from the operating physician's patient list. Phase three processes the patients from their arrival until they are discharged. Processing includes pre-surgery preparation, surgery, post-surgery recovery any inpatient stay and discharge. Finally the fourth phase rebuilds the surgeon's waitlist. The completion of each day signals a function to rebuild physicians operating list. Rebuilding physician waitlists at the end of each day ensures a waitlist of constant length. The choice of modelling waitlist at first seems impractical since waitlists are dynamic, but in doing so it allows the model to pull from historical patient mixes and use historical cancellation rates to determine the daily operation list. In EH's case where current waitlist data is opaque this method reduces modelling time and limits model assumptions, instead utilizing historical data. Figure 10 graphically presents the four phases on the simulation model.

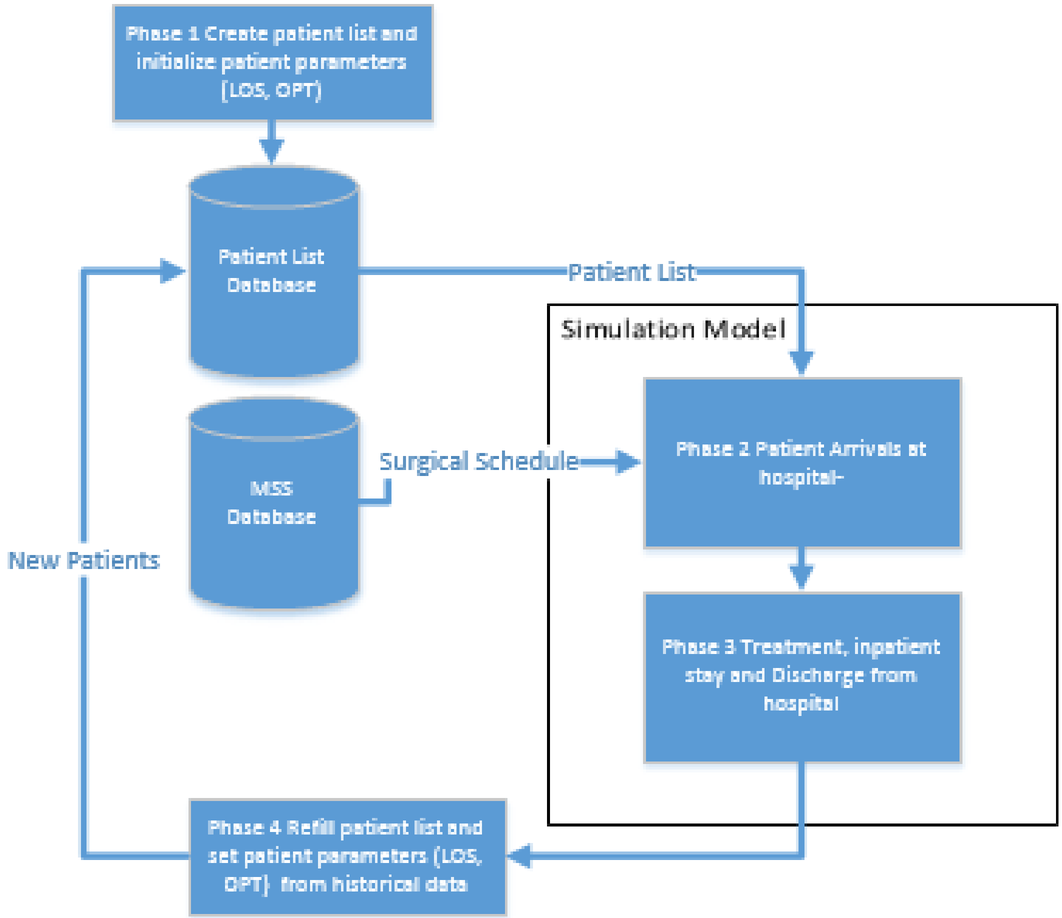

Figure 11 Simulation Model Phases

6.3.4 Modelled Resources

The simulation models three primary resources at both the HSC and SCM. The modelled resources include surgeons, operating rooms and the post-operation bed resources. This section will discuss in detail how surgeon schedules are modelled, how operating rooms are utilized and the use of bed resources.

6.3.4.1 Surgeon’s Schedules

Surgeons are an essential hospital resource and surgeon schedules are a main driver of patient flow and bed utilization. In the model the assignment of surgeons to patients is determined by the MSS. A sample schedule is shown in Figure 11. In the sample schedule surgeons are assigned an entire OR block except for the highlighted “difficult cells”. These OR blocks represent the case when the OR block is not assigned to one surgeon. Instances include when the block is split into morning and afternoon slots or when it rotates between multiple surgeons or when it is assigned to an entire surgical designation. When these instances occur the model proportionally selects a surgeon from a group of surgeons who have previously operated during that OR block based on historical usage rates for that OR block. When a surgeon is assigned an OR block a daily list of patients is selected from the waitlist. On days when an OR block is split into half blocks the model reduces the patient list accordingly. Each surgeon is responsible for selecting which patients to operate on based on severity and urgency. The simulation model selects patient type proportional to each surgeon’s historical patient mix. A selection algorithm determines which patients and what quantity of patients will be operated on each day. The modelled patients are initially selected first in first in first out based on their place on the waiting list and. The selection algorithm looks to find a patient mix whose expected operation length fits within a confidence interval of historical daily operation times, if the patient mix exceeds this time, a patient is randomly selected to be not booked for that day. The selection algorithm is described in detail in section 6.3.5.

MSS Hospital A							
Day	1	2	3	4	5	6	7
OR 1	Surgeon A	Surgeon B	Surgeon C	Surgeon D	Surgeon E		
OR 2	Difficult	Surgeon F	Surgeon G	Surgeon F	Surgeon B		
OR 3	Surgeon H	Surgeon I	Difficult	Surgeon J	Difficult		
OR 4	Surgeon K	Surgeon L	Surgeon M	Surgeon N	Surgeon O		
OR 5	Surgeon N	Surgeon P	Surgeon Q	Surgeon R	Surgeon S		
OR 6	Surgeon T	Surgeon U	Surgeon V	Surgeon U	Surgeon V		
OR 7	Surgeon W	Surgeon X	Surgeon Y	Surgeon Z	Surgeon Z		

Figure 12 sample input schedule

On days when a surgeon is not scheduled it is still possible for them to operate. This occurs when a surgeon is on call and is required for a non-electing emergency surgery. The model determines on-call surgeons by proportionally selecting a surgeon from each designation according to their historical emergency usage. Surgeons who are already scheduled for elective cases are exempt from being selected.

6.3.4.2 Operating Rooms

The model consists of 8 ORs at SCM and 11 at the HSC. The distribution of the operating rooms to surgeons is assigned to by EH administration to meet EH's needs. The utilization of operating rooms is controlled by the surgeons and therefore is tied closely to the schedule. In the model, operating rooms are assigned to patients when they enter the model according to the surgeon's OR block assignment. When the patient is ready for their operation they seize the OR until the operation is complete. The selection of which OR is controlled by the MSS which has restricted which rooms surgeons can operate in.

6.3.4.3 Recovery Beds

Post-surgery, recovery beds are seized by patients. The patients hold their bed resource until they are discharged. There are 103 beds at the HSC and 113 beds at SCM. If the capacity exceeds the number of available beds the two hospitals can temporarily alleviate the demand by using overcapacity beds. HSC and SCM are equipped with 60 and 27 overcapacity beds respectively. The overcapacity beds are designed for emergency cases and normal conditions are not designed to accommodate this level of patients. The simulation model examined two cases, one where the quantity of overcapacity beds were set to HSC and SCM levels and the second where the quantity was set to an artificially high number, as done in the MIP. The artificially high case is used to compare the results to the MIP and the actual rates to quantify the results.

6.3.4.4 Model Entities

Arena uses entities to control the flow of the model. Entities move between modules performing assigned commands. Commands include assigning attributes to the entity (i.e. patient's LOS), updating variables, assigning a route for the entity to follow and assigning which resources will be used for processing. The simulation uses five different types of entities.

The first type of entity is an initializing entity. An initializing entity is used to determine patient waitlists for each surgeon, for each surgeon that operates on that day, an initializing entity is created to refill that surgeon's patient waitlist. The second type of entity is a schedule reading entity. Schedule reading entities are created daily for each OR. The schedule reading entities schedule the model to read the schedule from the external database and assign patient entities their LOS, operation length, OR assignment and surgeon assignment. The third and fourth types of entities are the two patient types, elective and non-elective. These entities act as patients and flow throughout the model as described in sections 2.5.1 and 2.5.2 the final entity type is a statistic entity. Statistic entities are created daily to capture bed census data. The bed census statistics are critical because they are used to validate the model, compare results between the MIP and simulation and determine the impacts of the new MSS.

6.3.5 Model Flow

The model is broken into four phases:

1. Initialize
2. Creating the daily list of events (Inputting the MSS)
3. Patient Processing
4. Updating patient waitlists

The model uses Visual Basic to input data from an external database into the model. The Initialize phase creates patient waitlists. To do this an initializing entity is created for each surgeon to generate a patient waitlist for that surgeon. Surgeon waitlists are fluid with patients continuously being added from clinical assessments and being removed because they are unfit, no longer require the surgery or after the operation is completed. Blake (2005) outlines many of the historical difficulties with modelling data from current patient waitlists [27]. Acknowledging the difficulty in trying to replicate patient waitlists, each surgeon’s patient waitlist is instead based on the each surgeon’s historical patient mix. Historical patient mixes were determined by analyzing two years of historical data on the types of surgery, the frequencies of those surgery types, the associated lengths of operations and LOS.

The second phase of the model is inputting the MSS. In this phase a schedule reading entity is created for each OR in the system daily. The entity reads the MSS which is stored in the database and assigns which surgeons are going to operate and what patients they are going to operate on. In the model a selection algorithm is used to determine which patients the surgeon will select to operate on that day. A target daily operating interval was created for each surgeon based on their historical usage of their ORs. This allows the model to account for surgeons that tend to exceed the standard OR hours. The selection algorithm uses the average operation length and the average time between patients to fit the operations within the target daily operating interval. The selection algorithm begins by adding the first patient on the patient waitlist to the daily operation list. If the total expected operating time is less than the minimum target time than an additional patient is added. If the total expected operating time exceeds the maximum value of the target operating interval then the function randomly assigns a patient to leave the daily queue. The patient leaving the daily operating list is placed at the front of the surgeon's waitlist, but will not be selected again that day. By choosing a random patient to leave it eliminates the need to attempt to replicate a surgeon's logic and allows historical data to represent the surgeon's patient case mix. At each iteration the function checks the stopping criteria (whether the total daily OR time is within the target times). This process is repeated until the stopping criterion has been met. The last step in this phase signals for the days' expected patients to be removed from the waitlist and to enter the hospital. The selection algorithm is illustrated below:

Step 1 Total OR time = 0

Step 2 Select patient in position 1 from waitlist and add to selected list.

   a. Total OR time = Total OR time + operating groups average OR time

Step 3 Is the total OR Time within the target values

a. Yes go to Step 8

b. No go to Step 4

Step 4 Check if total time is less than minimum target

a. Yes go to step 5

b. No go to step 6

Step 5 Select patient in position 1 unless they have already been selected from waitlist and add to selected list.

a. Total OR time = Total OR time + operating groups average OR time + average time between patients

b. Return to step 3

Step 6 Remove random patient from daily operation list

Step 7 Return to step 3

Step 8 End

A given patient can only be removed from the daily operating list three times before the model forces that patient to be selected.

The third phase of the model is processing patients. This phase consists of both inpatients and outpatients and includes pre-surgery, surgery and post-operative care. Elective patients are determined as described in the second phase. Non-elective patients enter the model according to their historical arrival rates into the OR. These patients are assigned a surgery type, a physician, a length of operation (OPT) group and a LOS group. From this point all patients follow the same process. They are delayed for pre-operative care. Once a patient is ready for surgery they seize a surgeon and an OR until their operation is complete. Once the patient exits the OR, the model will delay the next patient from entering based on the historical times between patients exiting and entering the OR for a given surgical specialty. Once this time elapses, the next patient will enter the OR and the process continues until one of the following conditions is met:

1. The surgeon has no more patients to operate on
2. The operating time has exceeded the allowable limit and the model decides to cancel the surgeon's remaining surgeries
3. The patient is an inpatient and there are no more bed resources available for the patient post-surgery.

Following the operation the patient proceeds to post-operative care. After post-operative care patients can either be discharged (outpatients) or they will occupy a bed resource at their designated hospital. Patients occupy their bed resource until they have exceeded their LOS. After surgery patients are assigned a probability of requiring additional add-on surgeries. If the patient requires additional surgeries they may go immediately back to the OR for a follow-up surgery or to an inpatient ward until a surgeon is available or they are ready for the surgery. At the end of their LOS all patients are discharged at 8:00 am freeing up their bed resource. The discharge process is complex with multiple nurses working together, to complete the discharges on top of their other responsibilities. Actual discharges are spread throughout the day and dependant on nursing teams and families to coordinate, because of this complexity a decision was made to have all discharges occur at 8:00 am. By discharging all the patients simultaneously the model ignores the discharge procedure and is able to isolate the impacts of the MSS from the discharge procedure. Any time of day prior to the end of the day could have been selected since the cumulative patient bed days are only being analyzed at the end of each day. This assumption has an additional benefit of providing a more direct comparison to the MIP results.

The final phase of the process is the rebuilding surgeon’s patient waitlists. At the end of each day, an initializing entity is generate for each surgeon that operated and the model simply refills the waitlist by randomly generating patients from the surgeon’s historical case mixes. This process functions similar to Phase 1.

6.4 Comparing the Simulation and MIP

The MIP is used to evaluate MSSs to find the optimal set of MSSs to minimize overcapacity beds. The simulation model quantifies the results of the selected MSSs. The results between the two models are compared to adjust patient LOS in the MIP to synchronize the models outputs to account for underestimates that come from using historical averages. This section provides Table 2, which summarizes the differences between the two models.

Model Characteristic	Simulation	MIP
Daily Operations	The quantity of operations for each surgeon is calculated each time a surgeon has an assigned an OR block and determined based on selection algorithm described in Section 6.3.5	Constant quantity for each surgeon based on their historical average of operations per day
Emergency Patients Arrivals	Arrive according to historical arrival rates into the surgery department.	The total quantity of MIP beds is reduced by the historical daily average of Emergency patients occupying beds
Hospitals	SCM and HSC modelled as Hospital 1 and Hospital 2	SCM and HSC modelled as Hospital 1 and Hospital 2
LOS	Randomly determined from a distribution fitted to historical date for each surgeon as described in Section 7.4.4	For each surgeon (S), LOS determined by: $LOSS = \mu LOSS + F^{*}\sigma LOSS$. Where F is an adjustment factor used to synchronize the results between the two models. $F_i = F_{i-1}$*(overcapacity bed days Sim/ overcapacity bed days MIP) for each i>1
Overcapacity Bed Quantity	Run for two scenarios: 1. ∞ for direct comparison with the MIP 2. 60 for HSC and 27 for SCM to quantify results	∞ to capture the total quantity of overcapacity beds generated from the MSSs being evaluated
Patient Discharge	All patients are discharged at 8am each day. A patient is ready to be discharged if their quantity of days in the hospital is greater than their assigned LOS and they do not required additional surgeries	All patients are discharged on day D if the quantity of days they have been in the hospital is greater than their assigned LOS
Patient Selection	Patients are selected by selection algorithm described in Section 6.3.5	Each surgeon only produces one patient, which is repeated for each of their daily operations
Quantity of ORs	Hospital 1: 7 Hospital 2: 11	Hospital 1: 7 Hospital 2: 11
Schedule	Utilizes MSSs generated by the MIP	Evaluates many possible MSSs, limited by model constraints
Statistic time Period	Statistics collected as a snapshot at the end of each day.	Days
Time in OR	Random selection from historical case mix for each surgeon as described in Section 7.4.3	OR Time is not considered

Table 2 Comparing Model Characteristics between the Simulation and the MIP

Chapter 7. Data

The data for this project was collected from three main databases: Meditech, PICIS OR system (PICIS) and the Discharge Abstract Database (DAD). Data was examined over a two year period starting in September 2012. The following subsections will discuss the data sources, how the data was analyzed and how it was inputted into the model.

7.1 Data Sources

Meditech is Eastern Health's central database for employees; containing information ranging from wages to patient records and bed utilization. Within Meditech is a bed board for each hospital that provides an instantaneous snapshot of the beds available and gives EH staff an indication when a demand issues may arise. Meditech was used to collect information on historical bed utilization, to provide information on the problem and to assist in validating the results of the simulation.

PICIS is Eastern Health's main database for OR visits. PICIS captures the operating hospital, OR, when the patient enters and exits the OR as well as descriptive information about the surgery. A summary of information exported from PICIS for this project is provided in Table 3.

Identifier	Description
Visit Identifier	A unique ID assigned for each visit
Hospital Site	The hospital at which the patient was initially treated
Procedure Date and Tim	A time stamp recording the date and time of the operation
OR	The operating room the patient was operated on
No. of Surgeries	The quantity of surgeries the patient received during their visit
Case Status	A classification of whether the surgery was elective, non-elective or an Add on
Case Procedure Category	A high level classification of surgery type i.e. Orthopedic
Case Procedure	A detailed classification of the surgery procedure i.e. ACL reconstruction
Case Surgeon	The operating surgeon
Enter Room Time	A time stamp recording when the patient entered the OR
Anesthesia Start Time	A time stamp recording when the anesthesiologist started treating the patient
Surgical Start Time	A time stamp recording when the operation began
Surgical End Time	A time stamp recording when the operation ended
Exit OR Time	A time stamp recording when the patient left the OR

Table 3 PICIS Database Data Summary

The DAD is used to collect information about patient visits and provide data to national organizations. The DAD is used across Canada at hospitals to provide standards and give hospitals' performance data to governing bodies and hospital management on how their hospitals compare to similar hospitals. The DAD was used to collect data on the patients LOS, ELOS, Case Mix Group and discharge statistics. The summary of data exported from the DAD for this project is provided in Table 4.

Identifier	Description
Visit Identifier	A unique ID assigned for each visit
Hospital Site	The hospital at which the patient was initially treated
Program Type	A high level classification of treatment. i.e. Surgery or Cardiac Care
Main Patient Service	A classification of the primary service provided i.e. Orthopedic Surgery
Case Mix Group	A detailed classification of the surgery procedure i.e. ACL reconstruction
Provider Service	im
Provider	The operating surgeon
LOS	The quantity of days the patient was in the hospital, including the day of their operation
ELOS	The estimated quantity of days the patient would be in the hospital including the day of their operation
Discharge Disposition	A classification of how the patient was discharged i.e. sent home or transferred to ALC treatment

Table 4 DAD Data Summary

Both PICIS and the DAD capture critical data to the MIP and simulation models. The data from the databases was analyzed by joining the two databases by Visit Identifier. The new data Table was analyzed and aggregated to determine Case Groups and historical distributions for lengths of operations and LOS.

7.2 Case Groups

For both the simulation model and the MIP Case Groups were used to aggregate the data. The data set had many individual points and Case Mix Groups and it was determined to be cumbersome and inefficient with so much stratification to input each of surgical Case Mix Groups. Instead the data was aggregated into Case Groups which could represent a subset of these patients and be fitted to a distribution. The number of Case Groups was determined through discussions with the Regional Director of Clinical Efficiency on which operations had similar characteristics and analyzing the data to determine similarities and a good fit to a theoretical distribution. The quantity of the Case Groups assigned to each surgical group is shown in Table 5.

Specialty	No Of Case Mix Groups
Cardiovascular	28
Oral/ Dentist	8
ENT	99
General	164
Gynecology	91
Neurosurgery	57
Ophthalmology	5
Orthopedics	101
Plastics	79
Thoracic	49
Urology	52
Vascular	57

Table 5 Case Mix Groups by surgery group

The MIP uses historical averages and standard deviations for each surgeon to determine the number of operations they will perform in each block and patient's LOS. ARENA Input Analyzer was used to fit Case Group to theoretical distribution. The aggregation resulted in 84 groups for operating time and 90 groups for LOS. In the simulation the operating time group is determined from the surgeon's historical case mix and subsequently randomly select the patients LOS group.

7.3 MIP Data Set

The MIP was constructed using historical averages for constant parameters. The choice to use a deterministic model with a simulation model was made because in practice simulation allow stakeholders to clearly visualize what is happening in the model thus validating the model more easily. The MIP uses days as its time period; therefore it is assumed that all surgeries and discharges are completed at the same time. Instead of using the operating time to determine how many patients will be seen in a day the MIP uses the historical average for each physician. For cases where a surgical block was not designated to a single surgeon (i.e. Urology rotating or more than two surgeons rotating a block) a replica surgeon was created to represent each unique case. The values for the replica surgeon are based on the historical data set for that OR block. Similarly average values were used for patient LOS parameters. Average values have been shown to underrepresent capacity issues, which was demonstrated using the simulation model.

7.4 Simulation Data

The simulation uses a centralized data source to determine each patients operating time, LOS, their physician and OR. Simulation can represent random data in three ways. The first is to simply reproduce existing data within the simulation. This method is less preferred since it can only provide results for one specific case. The second way is to use the data to generate empirical distribution functions for each random variable. The third and most preferred method is to use the data to generate a theoretical distribution and use hypothesis tests to determine if it is a good fit. For the simulation datasets theoretical distributions were used if a theoretical distribution was determined a good fit for the historical data. In instances when a good fit did not exist then an empirical distribution was used.

7.4.1 Fitting Distributions

Data was joined from PICIS and the DAD and aggregated into Case Groups based on similar characteristics for both operating time and LOS. Each Case Group was tested for a good fit of a theoretical distribution. Before testing distributions against the historical data set, the data was compared between surgeons and operating sites to see if there were statistical differences. If no statistical differences existed, then one distribution could be fitted for the group. In cases where there were statistical differences then a unique distribution was fitted for each exception. Fitting the groups to distributions was done using Arena's input analyzer. The data was first plotted into a histogram similar to Figure 12 to generate an initial hypothesis to what distribution would might fit the data.

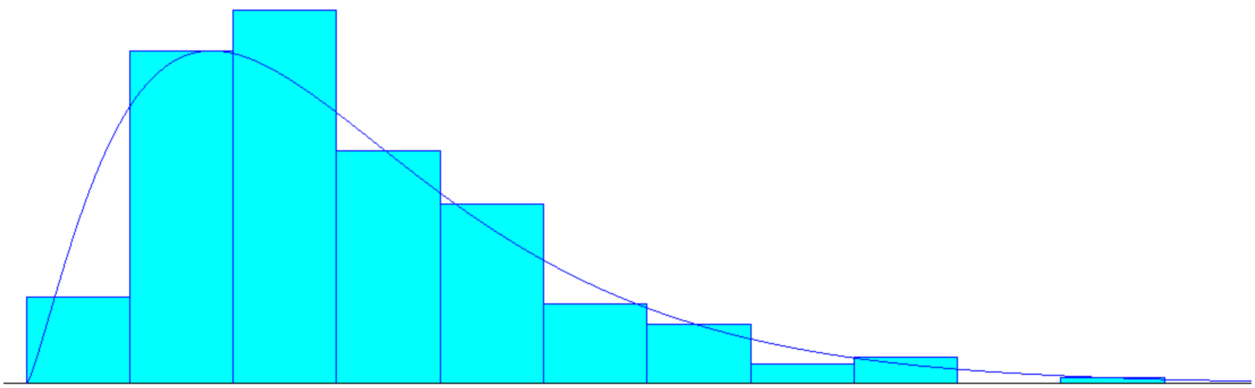

Figure 13 A sample of Input Analyzer's plotted histogram

Input analyzer then applied K-S and Chi-goodness of fit tests. Input analyzer reports acceptance probability uniquely, a minimum probability of 0.05 in is considered to be a good fit by Rossetti [28]. If more than one distribution met the requirements than the one with the best fit was selected. If no distributions had a minimum probability greater than 0.05 then an empirical distribution was used. This method was applied to operating time, LOS, arrival rates and the time between surgeries.

7.4.2 Operating Room Time

The operating room time was examined and fitted to a distribution for each Case Group. The time spent in the operating room was determined by subtracting the time the patient entered the OR from the time they exited, thus capturing their entire duration. For surgical groups that operated at both sites including general, orthopedic and plastic each Case Group data was separated by hospital site. For case groups operating at both sites, a Z test was completed for $\alpha = 0.05$ and it was determined that five case groups had statistical differences. For these groups a different distribution was used at each site and for all other Case Groups the data. For non-elective surgeries the data was similarly aggregated and fitted into distributions.

7.4.3 Daily Operation Time

The daily operation time was likewise examined for each of the surgical specialties. The number of patients selected by each surgeon was determined by fitting the average operating times of the patients in the waitlists within target operation times for the surgical group. The surgical group's target times were based off of historical data of their daily operation times. The average operating time, standard deviation and quartile data for each surgical specialty is shown in Table 6.

Case Procedure Category	Average	1ST QUARTILE	3rd QUARTILE	Max	Standard Deviation
CARDIOVASCULAR SURGERY	451.2	304.5	593.0	824.0	163.1
GENERAL SURGERY	337.8	222.0	448.0	914.0	145.7
GYNECOLOGY SURGERY	126.2	32.3	216.8	282.0	89.7
HEAD AND NECK SURGERY	356.1	253.0	452.0	909.0	144.5
NEUROSURGERY	352.8	286.0	437.0	632.0	116.2
ORAL SURGERY	359.9	304.0	440.0	573.0	110.9
ORTHOPEDIC SURGERY	353.1	283.0	448.0	937.0	128.4
PLASTIC AND RECONSTRUCTIVE SURGERY	340.6	262.0	427.0	663.0	121.3
THORACIC SURGERY	327.1	241.3	415.0	600.0	120.8
UROLOGY SURGERY	360.7	316	435	891	122.7
VASCULAR SURGERY	313.9	224.3	415.1	578.0	120.9

Table 6 Daily Operation Time Summary (Minutes)

7.4.4 Patient LOS

For patient LOS, data analyzed and fitted to a distribution for each Case Group. For the surgical groups that operated at both sites, the data was separated and analyzed in the same way as described in Section 7.4.2 for Operating Room Time. Three Case Groups were determined to have statistically significant differences. For these Case Groups two separate distributions were used for each site. The process was repeated for non-elective surgeries.

7.4.5 Time Between patients

Analyzing the data set, it was apparent that there is commonly a period of time between when one patient exits the OR and the next patient enters. This time between patients is critical to replicating the quantity of operations that a surgeon can be expected to complete. The time between patients is not directly captured by the data set, but could be extracted by analyzing subsequent operations for surgeons. To do this patients were sorted by OR, date of their operation time and the time they entered the OR. The time between patients data set was used in the simulation in two ways. The first, uses the median time between the patients for each specialty in determining the total expected daily operation time. The total expected daily operating time needs to fit in between the set operating targets to be an accepted daily list patient list. The second uses the distribution for each surgical specialty in the model to delay the next patient from entering the OR. The time between patient's data is summarized in Table 7.

Surgery Type	Cases Examined	Median Time Between Patients (minutes)
CARDIOVASCULAR SURGERY	103	28
HEAD AND NECK SURGERY	210	21
GENERAL SURGERY	250	26
GYNECOLOGY SURGERY	27	20
NEUROSURGERY	175	11
ORTHOPEDIC SURGERY	532	25
PLASTIC AND RECONSTRUCTIVE SURGERY	85	28
THORACIC SURGERY	64	34
UROLOGY SURGERY	248	27
VASCULAR SURGERY	101	27

Table 7 Time between Patients Data Summary

7.4.6 Arrivals

Historical information was used to model patient arrivals. Both elective and non-elective patient arrivals were modeled. The next two subsections will describe how the arrival process was modelled.

7.4.6.1 Elective Patients

The rate of arrivals for elective patients is determined by which surgeons are operating and the number of patients they select to perform surgeries on. The modelled surgeons are assigned an initial patient waitlist of 30 patients which are created based on their historical patient mix. This means that if a surgeon historically perform 60% knee replacements than the make-up of the surgeon's waitlist overtime will accurately reflect this. Each day when a surgeon is assigned an

OR block, a selection algorithm as described in section 6.3.5 is used to determine the surgeons list of patients. The algorithm was written in Visual Basic and used average operating times and times between surgeries to determine the number of patients that they would select. The objective of the algorithm is to find a mix of patients that fits within the surgeons target times for operation length. If the subset of patients did not fit the algorithms requirements than a random patient was removed and a new one added. This process was repeated until a patient mix fit the requirements. The removed patient would be placed at the head of the surgeon's queue and the model recorded the amount of times that a patient was removed. After a set number of removals the patient was forced into the schedule and could not be removed.

7.4.6.2 Non-elective arrivals

Non-elective patients arrive after being referred by a doctor working in the Emergency Department or from another service in the hospital such as Medicine. For the purpose of this research, non-elective patients are only captured at the time they enter the OR. This means that patients that arrive in emergency, but do not have a resulting surgery during their visit are not considered. Historical OR data shows that the arrival of non-elective patients is varied throughout the day. The average quantity of non-elective surgery patient arrivals at HSC and SCM between September 2009 and January 2015 is shown in Figure 13.

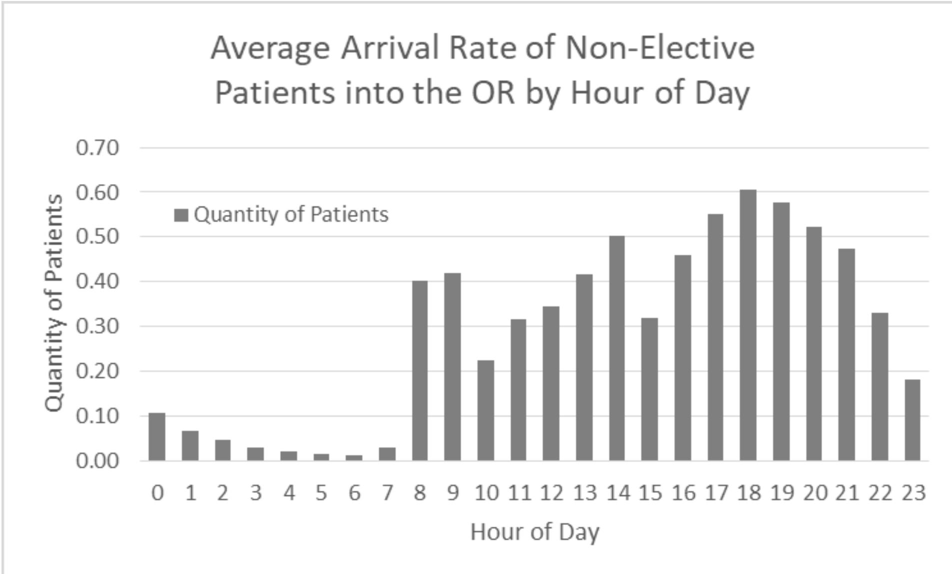

Figure 14 Arrival Rates of Non-Elective Patients into the OR by Hour of Day

It is evident from examining this figure that arrival rates vary by time of day. The arrivals were split into four time periods: 00:00 - 07:00, 07:00 - 16:00, 16:00 - 21:00 and 21:00 - 00:00. The data was fitted to a distribution by arrival rates or the time until the next patient arrives. The model reflects the historical breakdown between facilities where historically 39% of emergency patients arrive at SCM and 61% at HSC. The percentage of arrivals by surgical group is summarized in Table 8.

Surgical Group	Percentage of Emergency Arrivals
CARDIOVASCULAR SURGERY	2.5%
GENERAL SURGERY	41.9%
GYNECOLOGY SURGERY	2.6%
HEAD AND NECK SURGERY	2.4%
NEUROSURGERY	3.5%
ORTHOPEDIC SURGERY	31.9%
PLASTIC AND RECONSTRUCTIVE SURGERY	3.4%
THORACIC SURGERY	0.9%
UROLOGY SURGERY	4.9%
VASCULAR SURGERY	6.0%

Table 8 Percentage of Emergency Arrivals by Specialty

7.5 Initializing the System

Both HSC and SCM use three different MSS throughout the course of the year, each using regular, Christmas and summer schedules. The regular schedule which is the focus of this research is used from September 17th through June 15th excluding the three week Christmas schedule which operates between December 17th and January 4th. The summer schedule is used between the end and start of the regular schedule each year, which is used from September 4th through June 30th. In the past the ORs have been utilized less during the summer schedule resulting in less bed demand. The average bed utilization for each month at both sites is plotted in Figure 14.

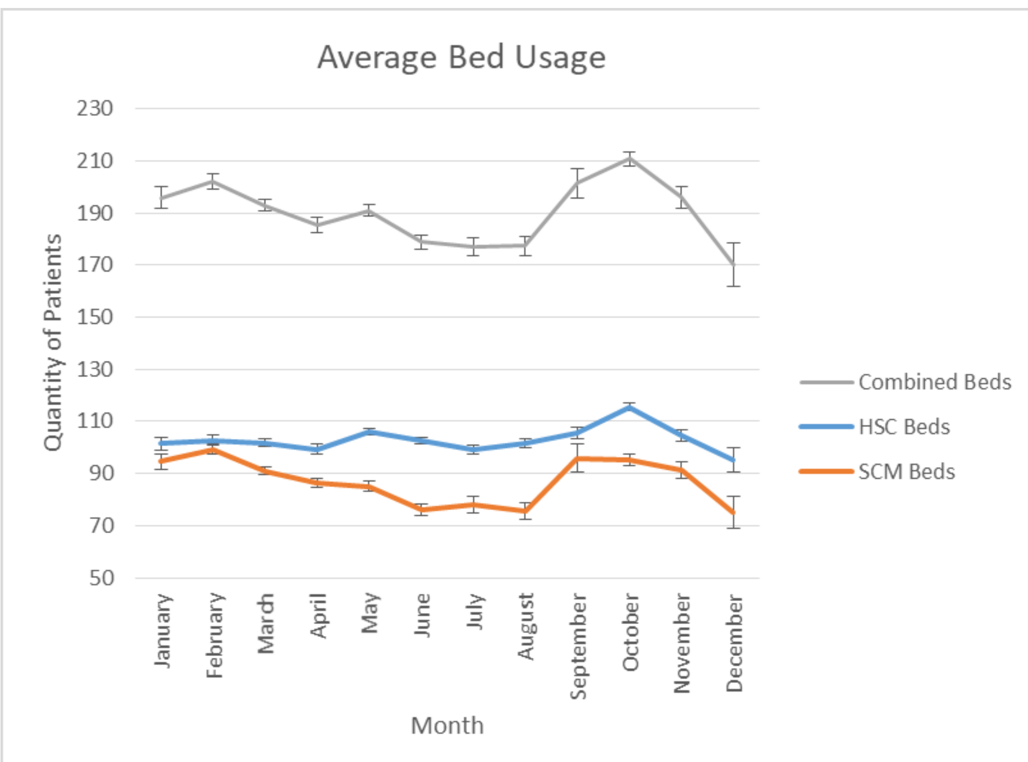

Figure 15 Average Bed Days

Figure 14 demonstrates fewer average bed days in June, July, August and December with the demand increasing again in September, October and January. Figure 15 shows the bed requirements from the beginning of July through the middle of October at the SCM in 2013. It indicates that when the regular schedule starts at the beginning of September that it takes the system a period of time before it approaches steady state.

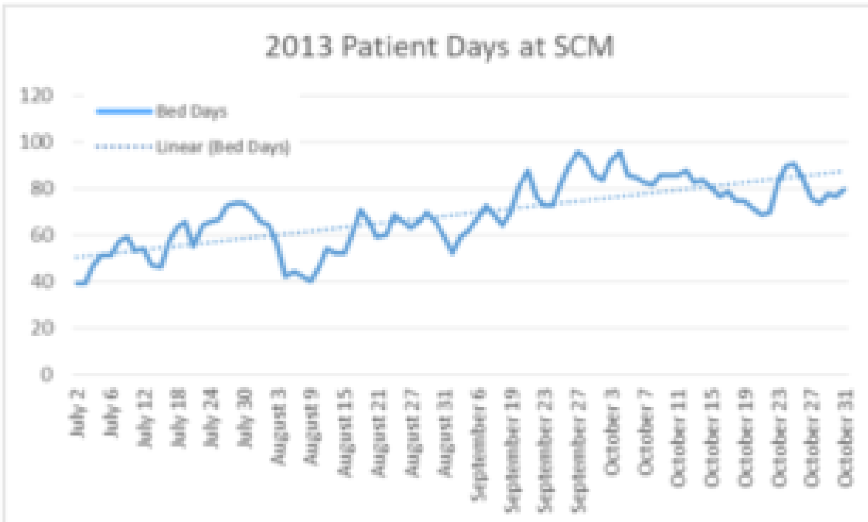

Figure 16 SCM Bed requirements August - October

EH is primarily concerned with the utilization throughout the regular MSS to effectively examine its impacts, the system must include a warm-up period where the model bed statistics approach the historical bed statistics at the beginning of the regular schedule, including the period prior to reaching steady-state.

To determine the appropriate warm-up period Welch's method of graphing the results was used. The number of beds used each day was exported to Excel for ten replications. The average between the ten replications was plotted and compared to Eastern Health's bed usage for the time period leading up to the regular schedule. Using Welch's method the bed statistics were determined to best approach historical statistics at the beginning of the MSS after a 43 day warm-up period. Each replication began on August 5, 43 days prior to the start of the regular schedule.

7.6 Validation

An effective simulation must accurately represent the system it is modelling. To demonstrate this, the results it produces must be shown to be in line with and reflect the system it is modelling. In this case, the simulation model was validated using Naylor and Fingers (1967) three step approach. Their three step approach is based on:

1. Building a model that has high face validity
2. Validating Model Assumptions
3. Comparing the model input-output transformations to corresponding input-output transformations for the real system.

High face validity equates to properly demonstrating the flow of patients throughout hospital operations and that operations are completed similar to the system being modeled. The flow of patients throughout the hospital was understood from past literature and discussions with EH's experienced staff. To validate the model flow, Arena's animation tool was used in conjunction with Visual Basic's debugging tool to step into the model step by step. Initially the model was broken down into subsections so that each component could be validated individually and then collectively as an entire system.

Validating model assumptions requires that the assumptions made that differed from the real system did not impact the results. Key model assumptions that needed to be validated include:

1. Discharges occurring at the same time of day
2. The determining of the on-call surgeons
3. Structuring the waitlists to always contain 30 patients.
4. Excluding overflow medicine patients

Discharging all patients at the same time of day removes the complexities of the discharge process from the model. To confirm that this assumption did not impact model results the volume of beds in use at the end of each day was selected as the metric. By examining bed utilization only at the end of each day, temporary excess in the data set caused by late discharges is removed.

On-call surgeon selection was based on the daily historical utilization of each surgeon. The historical data was used in conjunction to build a selection process. The quantities of on call surgeon selections in the model was compared to the historical rate for each surgeon. Using a t-test for $\alpha = 0.05$ there were no statistically significant difference between the two data sets.

Instead of using variable waitlists, the simulation model used a constant sized waitlist where patients are randomly created based on historical case mixes. Removing the waitlist and surgery selection logic from the model was done to reduce complexity while maintaining a patient mix built upon historical case mixes. To validate this assumption, patient LOS and operation lengths were compared using a t-test for $\alpha = 0.05$. There were no statistically significant differences in patient mixes shown using this approach.

The final decision to exclude the medicine departments overflow patients was made since these patients are not directly impacted from the MSS. These patients were simply removed from the historical bed statistics to compare the model's results.

The final validation step is comparing the model input-output transformations to corresponding input-output transformations of the real system. This was done through a series of t-tests where the two data sets were compared for $\alpha = 0.05$ and if necessary for $\alpha = 0.1$. The process was completed for each surgical group. Figure 16 shows the 95^{th} percent confidence intervals for each group for LOS. For each group, the confidence intervals overlap, indicating that there are no statistically significant differences for $\alpha = 0.05$.

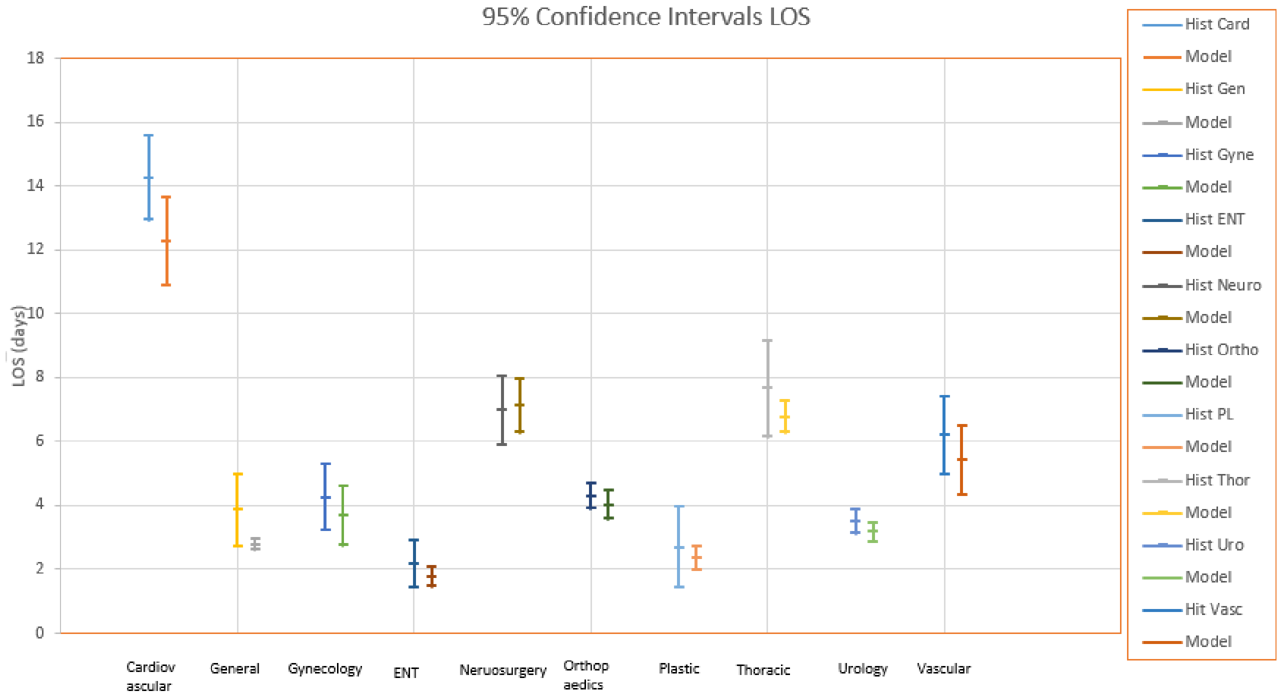

Figure 17 LOS Confidence Intervals

Similarly Table 9 shows the quantity of patients seen by each surgical group. At the 95th percentile this t-test does not demonstrate significant differences for all groups except for Vascular Surgery. Expanding the confidence interval for the Vascular Surgery Group shows that there is no statistically significant difference for $\alpha = 0.10$.

Specialty	2013-2014 Data	Model Data	Model CI High	Model CI Low
CARDIOVASCULAR SURGERY	260	248.5	260.16	236.84
GENERAL SURGERY	672	690.25	720.67	659.83
GYNECOLOGY SURGERY	24	28.5	33.09	23.91
HEAD AND NECK SURGERY	369	366.5	386.05	346.95
NEUROSURGERY	324	325.75	339.34	312.16
ORTHOPEDIC SURGERY	1006	999.25	1041.15	957.35
PLASTIC AND RECONSTRUCTIVE SURGERY	232	242	253.13	230.87
THORACIC SURGERY	121	119	123.5	114.5
UROLOGY SURGERY	501	512.5	557.85	467.15
VASCULAR SURGERY	222	252	270.2	233.8

Table 9 Patients Seen 95% Confidence Interval

The quantity of Emergency Patients that visited the hospitals is shown in Figure 17. The results do not demonstrate statistically significant differences for $\alpha = 0.05$.

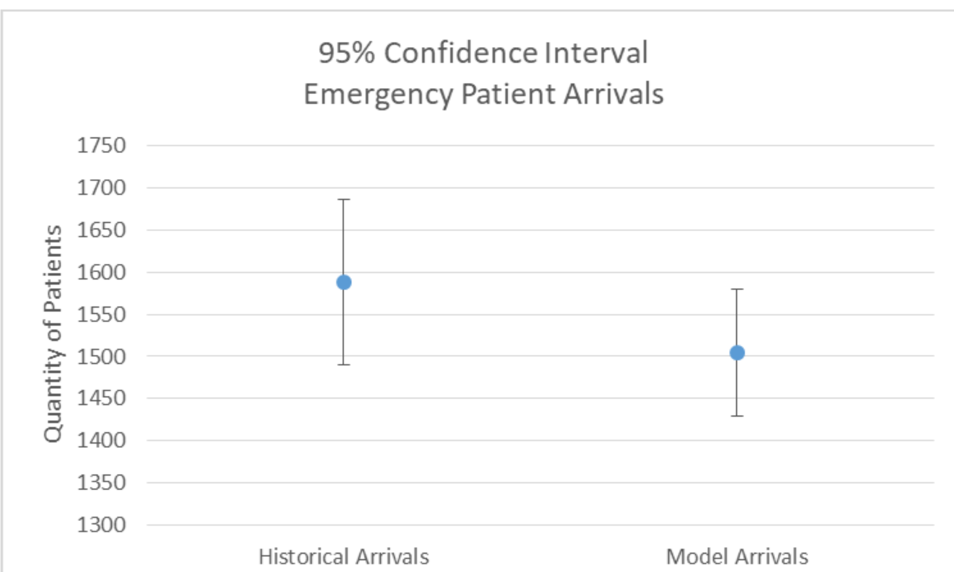

Figure 18 Emergency Arrival Validation

The final measure of validating the model is through examination of bed utilization. A t-test was completed and 95th percentile confidence intervals constructed for both sites. The results are compared in Figure 19.

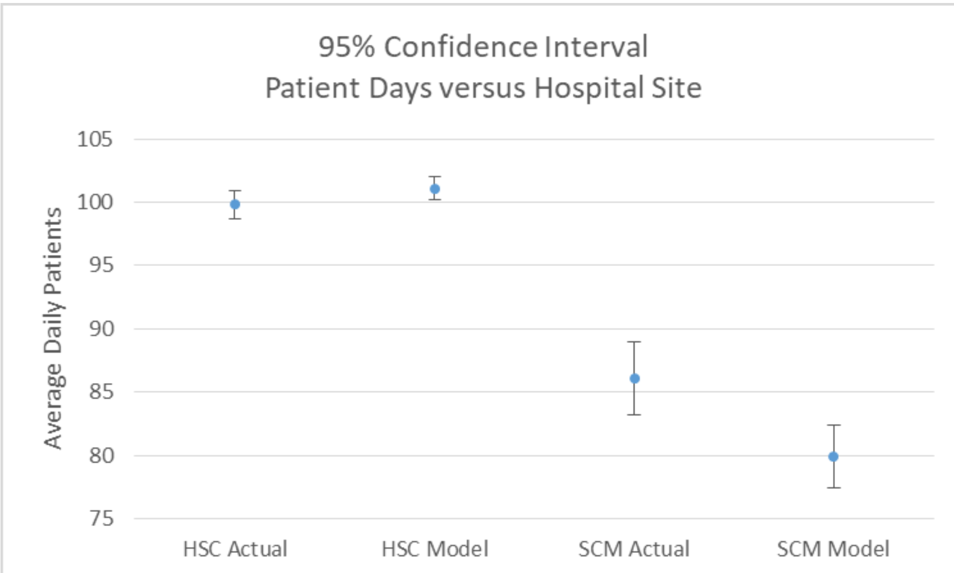

Figure 19 Daily Patients Seen

For HSC and SCM, no statistical significance was shown for $\alpha=0.05$ and 0.10 respectively. Based on the quantities of patients seen for each surgical group, patient LOS and emergency arrivals all being in line with historical values the slight discrepancy between the average daily modelled SCM patients and historical SCM patients is surprising. This discrepancy could be the result of many small differences in the two systems or potentially the result of something not captured in the data set.

Chapter 8. Results

This chapter presents the results from using the iterative approach described in Section 6.1 based on a MIP and simulation model applied as a case study to EH's St. John's hospitals. The MIP and simulation bed statistics were compared after each iteration and the MIP LOS adjusted as described in Section 6.1 until the differences in overcapacity beds were no longer statistically significant or the data sets stopped converging. Statistical significance was measured using the student's t-test for $\alpha = 0.05$. This chapter presents the differences between the two data sets and compares the EH's existing MSS with the various proposed MSSs from the MIP model.

The iterative approach was applied to three separate starting nodes. The starting nodes for the adjusted LOS in the MIP were arbitrarily selected as:

1. $\mu + 0.5\sigma$
2. $\mu + 0.75\sigma$
3. $\mu + \sigma$

In each of these cases the data sets never converged, getting caught in a suboptimal loop where the adjustment factor F went back and forth between approximately 0.1 and 1.4. An example using 1σ as the starting node is shown in Table 10:

Iteration	Standard Deviations Added to Average	MIP	Simulation	Adjustment
0	1.000	4070	407	0.100
1	0.100	32	458	14.313
2	1.431	5378	406	0.075
3	0.108	35	452	12.914
4	1.395	5348	408	0.076
5	0.106	35	452	12.914
6	1.375	5330	448	0.084

Table 10 A Sample of Iterative Approach

After not converging the data sets with multiple starting points, the MIP and simulations were run for many scenarios exploring the solution set to determine what F values in

[1] $LOS_S = \mu LOS_S + F^*\sigma LOS_S$ for each surgeon S

would the two data sets converge and to evaluate if varying F could provide better MSSs as measured by the simulation. The results for the MIP and Simulation Results, varying the Adjustment Factor in $\mu + F\sigma$ from 0 to 1 are shown in Figures 19 and 20:

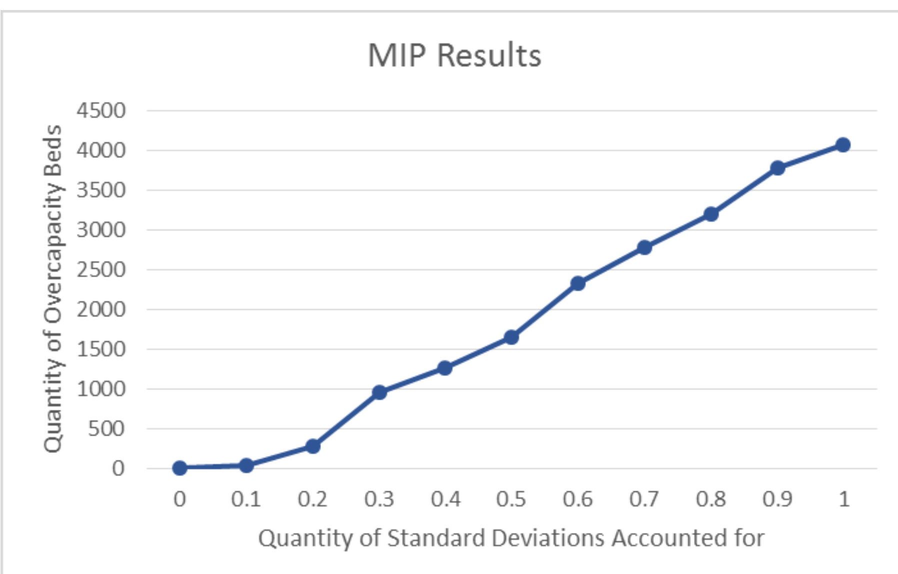

Figure 20 MIP Results

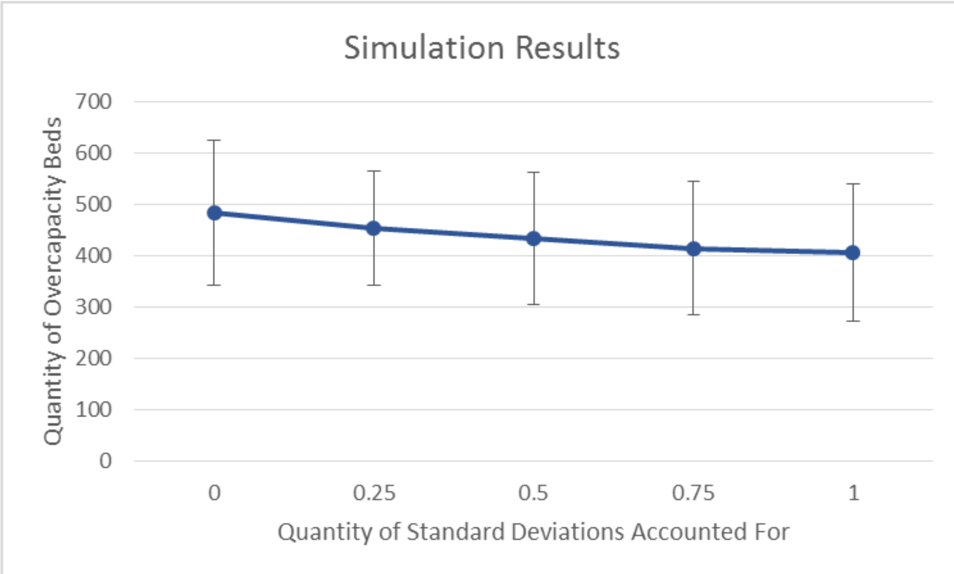

Figure 21 Simulation Results

The MIP results increase almost linearly by account for more of the historical standard deviation, where the simulation results appear to trend downwards. The increase in the MIP overcapacity bed days intuitively makes sense because the longer a patient stays the more patient bed days.

In the case given the data sets provide converging results between 0.225 and 0.25 standard deviations. The simulation results seem to indicate that the more standard deviations accounted for, the better the resulting MSS, although the results are statistically insignificant for $\alpha = 0.05$. This trend appears to level off after 1σ.

For comparative purposes, the resulting MSS from the MIP using 1σ was selected to compare the results between the EH's existing MSS and the proposed MSS. The contrasting MSSs are shown in Figures 21 and 22.

St. Clare's Mercy Hospital														
OR	Mon	Tue	Wed	Thu	Fri	Sat	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Sun
1	Felix	Thava	Cluett	Fitzpatrick	Drover C.			Felix	Dentist	Cluett	Tibbo	Drover C.		
2	ENT / Dentals	Browne	Smith C.	Browne	Thava			Cluett Full	Browne	Smith C.	Browne	Thava		
3	Melvin V	Cox	Heneghan/ Melvin	Heneghan	Heneghan/ MelvinV			Browne	Cox	Pace/Boone/Smith	Heneghan	Heneghan/ MelvinV		
4	Rockwood	Batten	Au	Tibbo	Stone			Rockwood	Batten	Au	Dentist	Stone		
5	ODea	Martin	Moores C.	Squire	Hogan G.			ODea	Martin	Moores C.	Squire	Hogan G.		
6	Gardiner	Pollett	Mann	Pollett	Mann			Gardiner	Pollett	Gardiner	Pollett	Mann		
7	Smith T.	Mathieson	Savoury	Burrage	Burrage			Smith T.	Redmond	Lee	Burrage	Burrage		
Health Science Center														
OR	Mon	Tue	Wed	Thu	Fri	Sat	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Sun
8	Oleary	McEachren	McNicholas	Murphy	Willams			Oleary	McEachren	McNicholas	Murphy	Willams		
9	Jacman	Whelan	Dunphy	Whelan	Pace/Boone/Smith C			Jacman	Whelan	Dunphy	Whelan	Cluett Full		
10	Fitzpatrick	Rideout	Seal	Jewer	Cluett			Fitzpatrick	Rideout	Seal	Jewer	Jewer		
11	Bohacek	Bohacek	Wells	Hogan M.	Pace			Gynecology	Bohacek	Wells	Hogan M.	Pace		
12	Au	ODea	Stone	Martin	Johnston			Au	ODea	Stone	Martin	Johnston		
13	Cluett SDC	Hogan M.	Boone	Mathieson	Opthamology			Radiation Onco	Hogan M.	Mathieson	Boone	Wells		
14	Hogan G.	Furey	Rockwood	Furey	Squire			Hogan G.	Furey	Rockwood	Furey	Squire		
15	Duffy	Hewitt	Drover D.	French	Gynecology			Duffy	Hewitt	Drover D.	French	General		
16	Avery	Maroun	Englebrecht	Maroun	Murray			Avery	Murray	Englebrecht	Maroun	Murray		
17	Lodge	Mong	Lodge	Melvin C	Melvin C			Lodge	Mong	Lodge	Melvin C	Melvin C		
18	Urology	Harvey	Mong	Fitzpatrick SDC	Fitzpatrick Full			Urology	Harvey	Mong	Cardiovadcular	Browne		

Figure 22 MIP Generated Schedule Standard Dev = 1

St. Clare's Mercy Hospital														
OR	Mon	Tue	Wed	Thu	Fri	Sat	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Sun
1	Stone	Dentist	Burrage	Tibbo	ENT / Dentals			Stone	Dentist	Burrage	Tibbo	Thava		
2	Heneghan/ MelvinV	Stone	Drover C.	Au	Boone			Savoury	Stone	Drover C.	Au	Boone		
3	Gardiner	Burrage	Melvin V	Heneghan/ MelvinV	Mann			Lee	Burrage	Melvin V	Gardiner	Gardiner		
4	Rockwood	Squire	Pollett	Furey	ODea			Rockwood	Squire	Pollett	Furey	ODea		
5	Squire	Rockwood	Martin	ODea	Redmond			Squire	Rockwood	Martin	ODea	Heneghan/ MelvinV		
6	Mann	Furey	Browne	Pollett	Hogan M.			Mann	Furey	Browne	Pollett	Hogan M.		
7	Heneghan	Smith T.	Batten	Martin	Au			Heneghan	Smith T.	Batten	Martin	Au		
Health Science Center														
OR	Mon	Tue	Wed	Thu	Fri	Sat	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Sun
8	Jacman	Willams	McEachren	Whelan	McNicholas			Jacman	Willams	McEachren	Whelan	McNicholas		
9	Oleary	Dunphy	Murphy	Opthamology	Whelan			Oleary	Dunphy	Murphy	Opthamology	Whelan		
10	Cluett SDC	Seal	Fitzpatrick SDC	Rideout	Jewer			Jewer	Seal	Fitzpatrick SDC	Rideout	Jewer		
11	Cox	Harvey	Gynecology	Murray	Drover D.			Cox	Harvey	Gynecology	Wells	Drover D.		
12	Browne	Wells	Hogan G.	Smith C.	Avery			Browne	Wells	Hogan G.	Smith C.	Avery		
13	Maroun	Maroun	General	Cluett Full	Bohacek			Maroun	Mathieson	Bohacek	Cluett Full	Bohacek		
14	Hogan M.	Thava	Moores C.	Pace/Boone/Smith C	Felix			Hogan M.	Radiation Oncology	Moores C.	Pace/Boone/Smith C	Felix		
15	Hewitt	Hogan G.	Duffy	Urology	French			Hewitt	Hogan G.	Duffy	Urology	French		
16	Englebrecht	Fitzpatrick Full	Pace	Johnston	Mathieson			Englebrecht	Thava	Pace	Johnston	Mathieson		
17	Melvin C	Browne	Melvin C	Lodge	Mong			Melvin C	Browne	Melvin C	Lodge	Mong		
18	Mong	Murray	Lodge		Urology			Mong	Murray	Lodge	Cardiovadcular	Urology		

Figure 23 Original MSS

The average quantity of patients at each facility is shown in Figure 23.

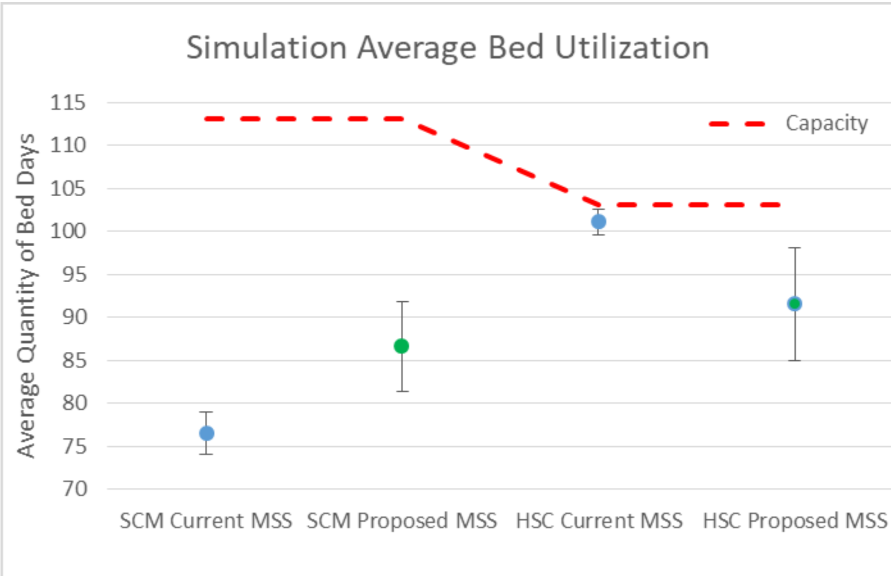

Figure 24 Simulation Average Quantity of Patients

For α = 0.05, the Proposed MSS results in statistically fewer patients at HSC and more at SCM. This results demonstrates improved bed balancing between the two sites. Figure 24 illustrates the quantity of overcapacity patients in the simulation model for both the Current and Proposed MSSs.

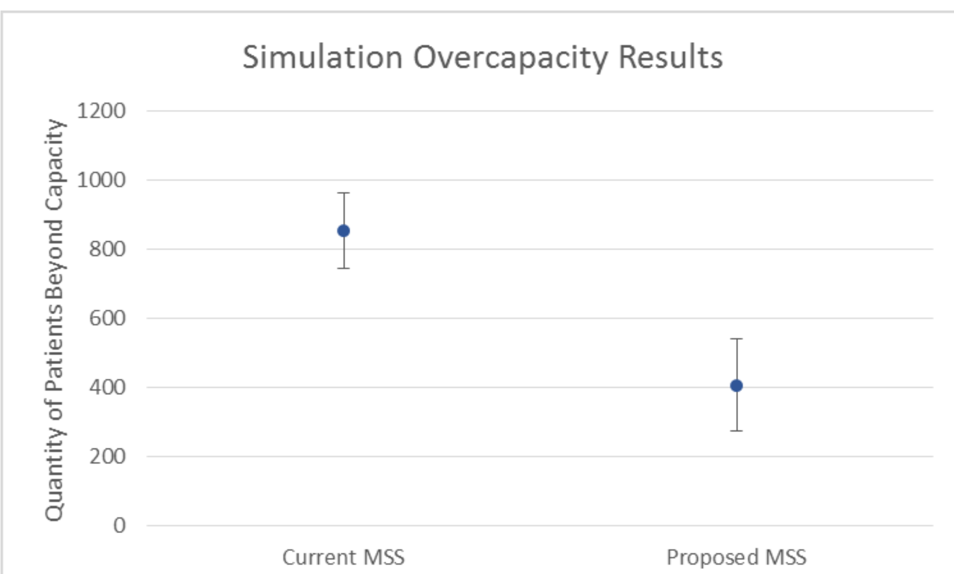

Figure 25 Quantity of Patients Served in Overcapacity Beds

The Proposed MSS need on average 47.7% fewer overcapacity beds. Table 10 summarizes the quantity of operations and patient data from the Simulations.

	Current		New	
	Value	Half Width	Value	Half Width
Add On Surgeries	300.2	19.84	309.2	18.06
Emergency Surgeries	1445.6	22.2	1443.33	10.92
Day Surgeries	3151	99.57	2968.27	69.6
HSC Total LOS	30456	683	28086.4	820.81
HSC Inpatients	1990	33.6	1766	45.23
SCM Total LOS	23229.3	762	25899.25	754.27
SCM Inpatients	1412	21.38	1859.25	25.27
Average Patients HSC	101.07	1.43	92.65	6.54
Average Patients SCM	76.51	2.41	85.33	5.22
Average Total Patients	177.58	2.95	177.98	2.56
Patients served beyond capacity (including excess)	852.8	109.92	407.27	132.96

Table 11 Simulation Results for the Proposed and Current MSS

Additionally Figures 26 and 27 illustrate better bed balancing between days at both sites. The new schedule produces the same trend as the historical data set, but significantly less variation between days. For the new MSSs both hospitals did not demonstrate statistically significant differences between day of the week for $\alpha = 0.05$.

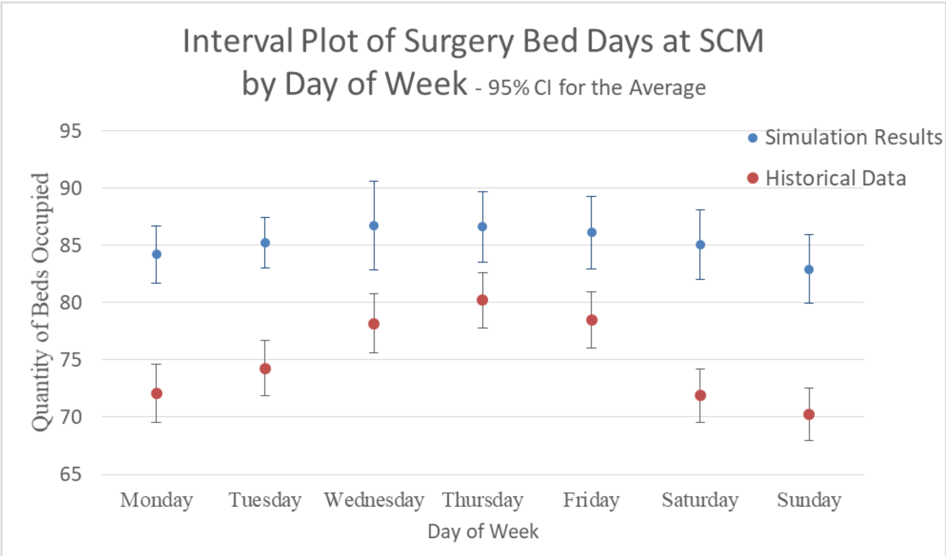

Figure 26 - Interval Plot of Surgery Bed Days at SCM by Day of Week

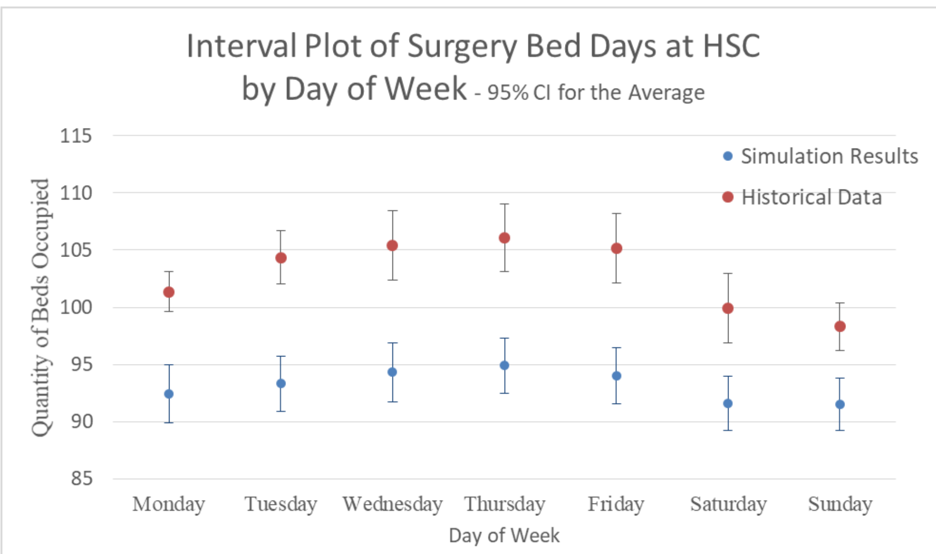

Figure 27 - Interval Plot of Surgery Bed Days at HSC by Day of Week

Chapter 9. Discussion

The purpose of this study was to demonstrate whether a two-step iterative approach using both a MIP and simulation could be used to approximate an optimal solution to better level bed capacity between a series of nearby hospitals. After each iteration the bed statistics are compared between the two models and MIP patient LOS updated for each surgeon by linearly adjusting the standard deviation multiple based on the differences in the two model outputs. Linearly adjusting surgeon LOS in the MIP this way resulted in a suboptimal loop. To fully explore the solution set the adjustment factor was instead manually incremented by 0.1 standard deviations and then fine-tuned as the approximations grew closer. The research was able to demonstrate the convergent results are possible using this method. Figure 20 shows a reduction in overcapacity bed days required, although not statistically significant for α =0.05, by increasing the patient LOS in the MIP to account for more variance. This could be because when the MIP is forced to account for more variance it must work harder to strategically place surgeons with more variability and thus find a solution for worse case scenarios.

Since the MIP results are strongly correlated to the adjusted patient LOS, where the simulation model LOS remains unchanged. As a result of this, the MIP results change significantly based on the adjustment factor and the simulation results are only impacted by the resulting MSS. An alternative to linearly adjusting could have been to reduce the size of the adjustment by scaling the adjustment factor down. An example is shown in the equation below:

[3] $F_i = F_{i-1} * 0.1 * (\frac{Overcapacity\ Bed\ Days\ Simulation}{Overcapacity\ Bed\ Days\ MIP})$ for each i > 1.

This change would account for the directional difference between the MIP and simulation, but reduced the significance of the adjustment on the MIP results.

This research was able to demonstrate that not accounting for variance in a MIP can result in suboptimal results and that in the case in minimizing overcapacity problems, accounting for more variance may even produce better results. This inherently makes sense since it is the worst case days that are the prime driver of overcapacity issues. The research was able to demonstrate that in a network of hospital pooling resources to develop a MSS can help reduce overcapacity issues.

The method of applying a MIP and simulation model in an iterative approach is consistent with past literature [20] and the results of this paper are similar to VanBerkel et al. (2011) which demonstrated improved bed levelness between wards using an OR Model [7] and Chow et. al (2005) who applied a Monte Carlo simulator to quantify the results of their IP generate schedule [26]. The results of this case study agree with research completed by the Fraser Health authority where bed demand between facilities was better balanced by pooling surgical resources [24] and with Belien and Demeulemeester (2007) who demonstrated the significance in accounting for variance when developing a MIP to level bed demand [22].

To solve the MIP several simplifications needed to be made. The following list identifies these limitations and explain why they were made and what impacts they had

1. The model used days as its time period. By using days as the time period the model ignores the timing of admissions and discharges. This will reduce congestion during periods when new patients are being admitted quicker than exiting patients are being discharged. The impacts of this process are critical to capacity issues, but are more significantly influenced by discharge procedures than the MSS.
2. The model focuses only on scheduled surgeries. This means that that the model does not account for emergency patients or patients that use surgery resources from a different

unit. This decision was made because although these other types of patients influence bed capacity it is difficult to predict and are not controlled by the MSS.

3. The model uses a two week planning horizon, by extending the planning horizon by a week half OR blocks can be changed to full blocks that surgeons operate every other week.
4. The MIP assumes the same patient mix for each surgeon each OR block they operate in. MIPs are not simulations and are limited to how they can reflect variance in a dataset.
5. In the MIP it is assumed that no surgeries are cancelled. The number of patients that a surgeon produces is identical in each OR block. By making this assumption the MIP excludes instance when a surgeon or patient need to cancel their appointment.
6. The model assumes there are infinite overcapacity beds. This allows the model to exclude potential overcapacity cancellations from its dataset and evaluate the impacts of the MSS. In practice there is only a finite quantity of overcapacity beds to accommodate patients.

Patient transfers occur when one site is experiencing excess capacity and there is a patient in stable condition who can be transferred with minimal risk. This practice is ignored in this model as and something EH expressed a need to move away from. Patient transfers are not captured in the data sets for this project because only the operating room and operating hospital are described for each hospital identifier. Patient transfers are not recorded in either the PICIS or DAD, as such it is speculated that the lack of patient transfers in the model contributed to the differences in the SCM bed utilization statistics.

The results of this research have been received by positively by EH, but with only a couple of months left in Calendar Year 2019 the resulting MSSs have not been implemented. Further discussions with key personnel will determine whether this methodology will be incorporated into generating future MSSs. The methodology used in this research does not give consideration to surgeon's clinical days or other scheduling constraints that surgeons may have. To successfully implement, surgeons need to commit to reshuffling their clinical days to accommodate the proposed MSS. Additional case studies investigating this method with practical results from real life implementations considering clinical significance are required to fully vet this methodology before it can be implemented at scale.

Chapter 10. Conclusion

The aim of this study was to apply a mathematical model to minimize inpatient congestions within a series of nearby hospitals. The methodology consisted of an iterative approach using both a MIP and simulation. The MIP used a multiple of patient LOS standard deviation for each surgeon to try and address MIP tendencies to underrepresent capacity requirements. After each iteration the MIP and simulation bed statistics were compared and a linear adjustment factor was applied to the MIP patient LOS for each surgeon based on the ratio of overcapacity bed days within each system. Although the results did not converge a manual adjustment was applied to get the data to converge. The resulting MSSs were all compared using the simulation and there was no statistical differences between them, but a trend indicated that up to 1 standard deviation that accounting for variance produced a better MSS. The resulting MSSs significantly reduced the requirement for overcapacity beds and provided improved balancing between the two hospitals.

This study presents a unique process to level bed demand between a series of hospitals to reduce inpatient congestion. The process is one of the first in the significant surgical scheduling problem literature that:

1. Examines nearby hospitals as a network that can pool resources
2. Accounts for variance through patient LOS standard deviation for each surgeon in a MSS optimization models.
3. Uses an iterative approach to converge results between MIP and simulation bed statistics by adjusting the quantity of patient LOS variance accounted for in the MIP.

Additionally the paper presents a unique patient selection algorithm to model daily patient mixes within a simulation model.

This research provides results for a case study. The extension of these methods to other hospital systems is required to better quantify its effectiveness. This research focused on surgical bed resources on hospital level, future research may want to consider on surgical bed resources for bed wards. This research has not considered several hospital resources including patient discharges, nurses, anaesthetists, clinical schedules or surgical equipment. An extension of this research would be to follow-up on the practical impacts of implementing the proposed MSS at EH to understand the full practical impacts of the recommend MSS. Making changes to a MSS has many practical considerations that need to be addressed including impacts to clinical schedules and surgeon preferences. Additionally research could be used to investigate the impacts of non-elective surgery arrivals in conjunction with MSS optimization and transfer between hospitals.

Bibliography

[1] "Indicators of Well-being in Canada: Canadians in Context - Aging Population," Government of Canada, 28 01 2015. [Online]. Available: www4.hrdc.gc.ca/.3ndic.1t.4r@eng.jsp?iid=33. [Accessed 28 01 2015].

[2] Health Council of Canada, "Progress report 2013: Health care renewal in Canada," Health Council of Canada, 2013.

[3] S. N. Soroka, "A report to the health council of Canada: Canadian perceptions of the health care system," Health Council of Canada, Toronto, 2007.

[4] J. T. Blake and M. W. Carter, "Surgical process scheduling a structured review," *JSHS,* pp. 16-30, 1997.

[5] J. H. May, W. E. Spangler, D. P. Strum and L. G. Vargas, "The surgical scheduling problem: current research and future opportunities," *Production and operations management,* vol. 20, no. 3, pp. 392-405, 2011.

[6] B. Denton, J. Viapane and A. Vogel, "Optimization of surgical sequencing and scheduled decisions under uncertainty," *Healthcare management sciences,* pp. 13-24, 2007.

[7] P. T. Vanberkel, R. J. Boucherie, E. W. Hans, J. L. Hurink, W. A. M. van Lent and W. H. van Harten, "Accounting for inpatient wards when developing master surgical schedules," *Anesthesia and analgesia,* pp. 1472-1479, 2011.

[8] K. Cattani and G. M. Schmidt, "The pooling principle," *Informs transactions on education,* vol. 5, no. 2, pp. 17-24, 2005.

[9] W. J. Hopp, I. M. Seyed and Y. Y. Gig, "Operations systems with discretionary task completion," *management science,* vol. 53, no. 1, pp. 61-77, 2007.

[10] C. Vasilakis, B. Sobolev, L. Kuramoto and A. R. Levy, "A simulation study of scheduling clinic appointments in surgical care: individual surgeon versus pooled lists," *The Journal of Operations Research,* vol. 58, no. 2, pp. 202-211, 2007.

[11] S. Mahar, K. M. Bretthauer and P. A. Salzarulo, "Locating specialized service capacity in multi-hospital network," *European Journal of Operational Research,* pp. 596-605, 2011.

[12] J. Magerlein and J. Martin, "Surgical demand scheduling a review," *Health science research,* pp. 418-433, 1978.

[13] J. T. Blake and J. Donald, "Mount Sinai Hospital uses integer programming to allocate operating room time," *Interfaces,* vol. 32, no. 2, pp. 63-73, 2002.

[14] D. Gupta and B. Denton, "Appointment scheduling in health care: challenges and opportunities," *IIE Transactions,* pp. 800-819, 2008.

[15] X. Yiting , L. Li, B. Zhuming, M. Wilamowska-Korsak and L. Zhang, "Operations research in service industries: a comprehensive review," *Systems research and behavioral science,* pp. 300-353, 2013.

[16] I. Marques, E. M. Captivo and M. Vaz Pato, "An integer programming approach to elective surgery scheduling," *OR spectrum,* pp. 407-427, 2012.

[17] D. Franklin and M. Alex, "Changing allocations of operating room time from a system based on historical utilization to one where the aim is to schedule as many cases as possible," *Anesthesia and analgesia,* vol. 94, no. 5, pp. 1272-1279, 2002.

[18] H. Aytug, M. A. Lawley, K. McKay, S. Mohan and R. Uzsoy, "Executing production schedules in the face of uncertainties: a review and some further directions," *European journal of operations research,* pp. 86-110, 2005.

[19] M. V. Calichman, "Creating an optimal operating room schedule," *AORN,* pp. 580-588, 2005.

[20] C. Banditori, C. Paola and V. Flippo, "A combined optimization simulation approach to the master surgical scheduling problem," *Journal of management mathematics,* pp. 155-187, 2013.

[21] N. Qing, P. Qingin and E. Tarek, "Improvement in the operating room efficiency using tabu search in simulation," *Business process management journal,* pp. 799-818, 2013.

[22] J. Belien and E. Demeuleester, "Building cyclic master surgery schedules with leveled resulting bed occupancy," *European journal of operations research,* pp. 1185-1204, 2007.

[23] V. S. Chow, L. P. Martin, N. Salehirad, W. Huang and D. Atkins, "Reducing surgical ward congestion through improved surgical scheduling and uncapacitated simulation," *Product and operations management,* pp. 3-39, 2011.

[24] P. Santibanez, B. Mehmet and D. Atkins, "Surgical blcok scheduling in a system of hospitals: an application to resource and wait list management in a British Columbia health authority," *Health care manage Science,* pp. 269-282, 2007.

[25] "A strategy to reduce hip and knee joint replacement surgery wait times in Newfoundland and Labrador," Newfoundland and Labrador Government, St. John's, 2012.

[26] V. S. Chow, M. L. Puterman, N. Salehirad, W. Huang and D. Atkins, "Reducing surgical ward congestion through improved surgical scheduling and uncapacitated simulation," *Production and Operations Management,* vol. 20, no. 3, pp. 418-430, 2011.

[27] J. T. Blake, "Shooting arrows in the dark: the policies and practices of waitlist management in Canada.," *Clinical and Investigating Medicine,* vol. 28, no. 6, pp. 308-311, 2005.

[28] M. D. Rossetti, Simulation modeling and Arena, Hoboken, NJ: John Wiley & Sons, 2010.

[29] "Eastern health project recognized for reducing wait times," 19 June 2013. [Online]. Available: http://www.thetelegram.com/News/Local/2013-06-19/article-3283973/EasternHealth-project-recognized-for-reducing-wait-times/1.

[30] Canadian Institute for Health Information, "National health expenditure trends 1975-2012,"

Canadian Institute for Health Information, 2012.

[31] T. Bryant, "An introduction to health policy," in *An introduction to health policy*, Toronto, Toba Bryant and Canadian Scholars' Press Inc, 2009, pp. 141-166.

[32] First Ministers, "First Ministers' Health Care Accord, A 10-year plan to strengthen health care," 2004.

[33] E. Erkut, A. Ingolfsson and G. Erdogan, "Ambulance location for maximum survival," *Naval research logistics,* pp. 42-58, 2008.

[34] M. W. Carter and S. Ketabi, "Bed balancing in surgical wards via block scheduling," *Minimally invasive surgical sciences,* vol. 1, no. 4, pp. 129-137, 2012.