Post COVID-19 Patient Throughput Simulation for Surgical Resource Allocation

by

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Table of Contents

Table of Figures

Tables

List of Abbreviations

NSH	Nova Scotia Health
PAR-NS	Patient Access Registry Nova Scotia
DAD	Discharge Abstract Database
NACRS	National Ambulatory Care Reporting System
DGH	Dartmouth General Hospital
HI	Halifax Infirmary
VG	Victoria General Hospital
HCH	Hants County Hospital
SSI	Scotia Surgery Inc.
CARD	Cardiology/Cardiac
GEN	General
NEURO	Neurology
OBGYN	Gynecology
OMFD	Oral Maxilla Facial Dental
OPHTH	Ophthalmology
ORTHO	Orthopedic
OTOL	Otolaryngology
PLAS	Plastic
THOS	Thoracic
URO	Urology
VAS	Vascular

Statement

In response to COVID-19, many elective surgical procedures in Nova Scotia were cancelled resulting in an increased waitlist. A discrete event simulation approach may provide strategies for waitlist management. Descriptive analytics of two years (2018-2020) of surgery data informed the model development. The model facilitated scenario analysis of recovery strategies, increased bed capacity and operating room (OR) hours, as well as the COVID-19 effects on room turnaround and demand.

The base model, which reflected the current system parameters, indicated the waitlist grew continuously with orthopedics, general surgery, and urology comprising 68% of the waitlist. The outpatient waitlist decreased to a steady state, whereas the inpatient waitlist continuously increased. The number of available OR hours and the types of patients on the surgical waitlist had the largest impact on the patient throughput. These aspects of resource allocation would positively impact the waitlist created by the COVID-19 pandemic.

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1 Introduction

The first cases of COVID-19 were reported on March 15, 2020 in Nova Scotia (Government of Nova Scotia Canada, 2020). As a response to the COVID-19 pandemic, most elective surgical procedures in Nova Scotia were cancelled on March 18, 2020 (Nova Scotia Health, 2020a) resulting in increased patient waitlist volumes. During this time emergency procedures and very high priority patients continued but a total of 3,212 surgeries were cancelled (Nova Scotia Health, 2020b). As the active case count decreased elective surgeries resumed. Figure 1.1 displays the number of active COVID-19 cases in Nova Scotia from March – September of 2020. The peak of the curve occurred in the middle of April and by the beginning of June there were little to no active cases. Due to the nature of the curve in Nova Scotia, elective surgical procedures began again in May. From the beginning of the pandemic until May 25th the surgical capacity was reduced to 25% of that of the previous year (Jerret, 2020). The surgical capacity slowly increased reaching 67% capacity by July 1st (Ray, 2020) and 97% capacity by August 24th (Grant, 2020).

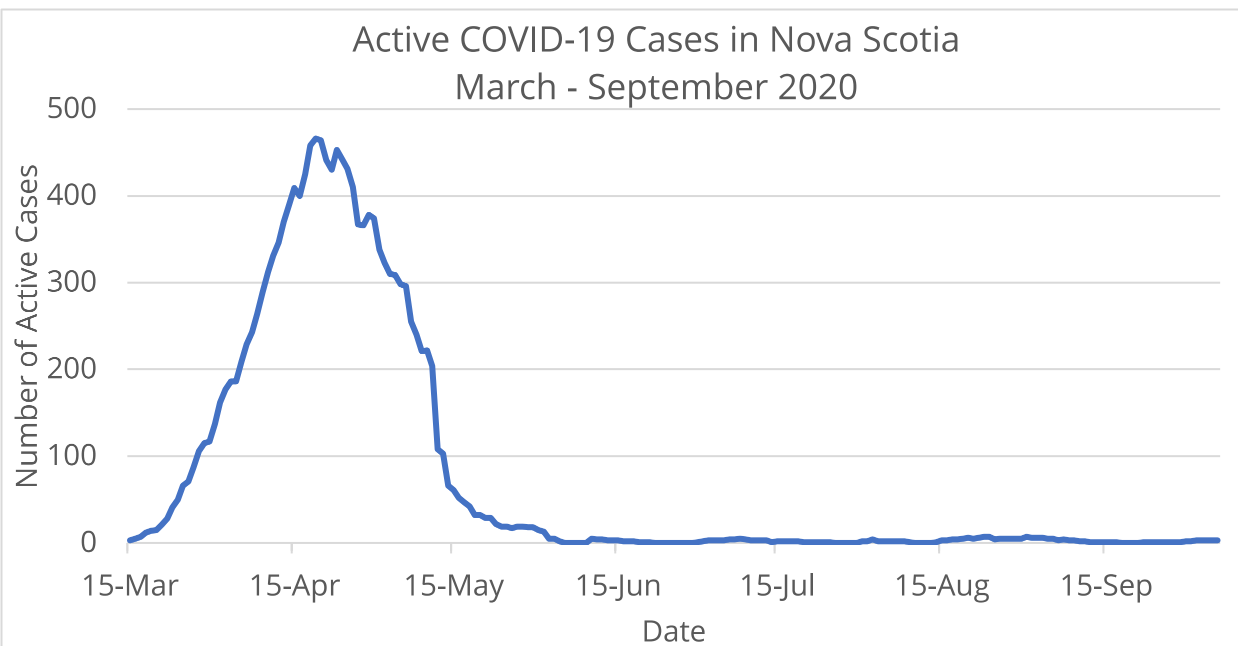

Figure 1.1: Active COVID-19 Cases in Nova Scotia March -September 2020

Due to the reduced capacity elective surgical procedures were not completed and therefore were not removed from the surgical waitlist at the same rate as pre-COVID-19. This, combined with the already well documented long wait times for some elective procedures in Nova Scotia, compounded the length of the waitlist and the wait time for patients. Additionally, during the first wave of COVID-19, surgical consultations as well as family doctor visits dramatically reduced. Surgeons were instructed not to conduct consultations in person, and many were not comfortable assessing patients using video conference. Many patients avoided in office visits to family doctors and were encouraged to conduct phone appointments when possible, due to the lack of knowledge surrounding COVID-19. Thus, the true waitlist size is comprised of three components: the waitlist prior to COVID-19, the surgeries cancelled due to COVID-19, and the not yet realized demand caused by the decrease in surgeon consultations and family doctor referrals. It was noted that due to the cancellation of surgical procedures some elective procedures that were already on the waitlist entered the system as emergency patients. This created an environment where patients were unable to access surgeries and caused the waitlist to grow.

An effective strategy is needed to address the compounded waitlist resulting from COVID-19. The overall objective is to provide direction for strategy development to allocate resources in the healthcare system. The climate within the healthcare environment created by the COVID-19 pandemic provides a "…once-in-a-generation opportunity to kindle a broader transformation of surgical services for a sustainable and ethical health system in Canada." (Urbach & Martin, 2020) An understanding of the impacts of resource allocation is crucial to effectively addressing the waitlist and developing new strategies that are not currently utilized by the healthcare system.

The objective of the research is to address the COVID-19 related backlog of elective surgery in Nova Scotia. The research identifies the current system configuration through data analysis to develop a base model. The overall throughput of the hospital is evaluated using the length of the waitlist over time as the metric. The waitlist is analyzed based on both the total waitlist as well as for each surgical specialty as each surgical specialty has specific demands. Experiments are developed to identify the impact of various levels of resources and demand on the overall throughput of the patients. The experiments developed address the out-of-the-box thinking required to reduce the surgical waitlist effectively and aggressively.

The remainder of this thesis is outlined as follows. Section 2 is a review of related surgery scheduling and capacity planning literature. Section 3 describes the methods and results used for the extensive data analysis. Section 4 illustrates the model development by outlining the current system and associated conceptual model and the simulation model. Section 5 describes the verification and validation methods used for the simulation model. The experiments developed and the associated results for the simulation model are outlined in Sections 6 and 7, respectively. Finally, Sections 8 and 9 discuss results and state the overall conclusions of the research, respectively.

2 Literature Review

There is extensive research applying engineering methods to surgery scheduling and capacity planning. This is not surprising as the surgical department "…constitute the largest cost center, and consume a large proportion of total expenses." (Lamiri, Grimaud, & Xie, 2009) The planning and scheduling of surgical patients is complex as it is dependent upon many resources within the hospital as well as being subject to unplanned emergency scenarios. The integration of the downstream and upstream surgical resources requires a wide scope of research which increases its complexity. Further, emergency surgery introduces a large degree of uncertainty too but are often not included in surgical scheduling and planning reviews (Cardoen, Demeulemeester, & Beliën, 2010). The aim of this chapter is to identify industrial engineering and operations research methods used to analyze surgical scheduling and capacity planning. The main objectives are to identify patient throughput strategies for surgical operations, and categorize the studies based on: focus; measurement metric; and methodology. Furthermore, applications of the research on the COVID-19 healthcare environment are also investigated.

The remainder of this section is structured as follows. The literature search methodology used is presented in Section 2.1. This section illustrates the database and key words used to complete the search and presents a PRISMA diagram associated with the search results. The subsequent sections categorize the identified articles based on focus (2.2), metrics (2.3), and methodology (2.4). The focus subsection categorizes articles based on review, surgical scheduling, and resource allocation. The metrics subsection reviews the most prevalent metrics used in the reviewed articles including patient wait time, patient throughput, resource allocation, and cost. The most commonly used methodologies used in the articles included simulation, mathematical programming, and simulation optimization, as discussed in the methodology subsection. The final section reviews the literature related to surgical scheduling and planning during the COVID-19 pandemic.

2.1 Literature Search Methodology

The search engine used was Google Scholar. It is important to note the search engine results method used by Google Scholar. "Google Scholar aims to rank documents the way researchers do, weighing the full text of each document, where it was published, who it was written by, as well as how often and how recently it has been cited in other scholarly literature." (Google Inc., 2017) The search strategy is illustrated in Figure 2.1 using a PRISMA (Preferred Reporting Items for Systematic reviews and Meta-Analyses) diagram (Liberati et al., 2009). The key words used in the search included 'wait list management', 'patient throughput', 'surgery patient throughput', 'OR throughput', and 'surgical wait list management' which produced 848 articles. The removal of the duplicates resulted in 802 articles. The 802 articles were screened which excluded 746 articles leaving 66 articles to be assessed. The articles were excluded because they were not related to surgery. The assessment of the articles removed eight articles as the articles did not discuss an analysis of a surgical waitlist. The remaining articles were studied, resulting in the 48 articles discussed in detail in this chapter.

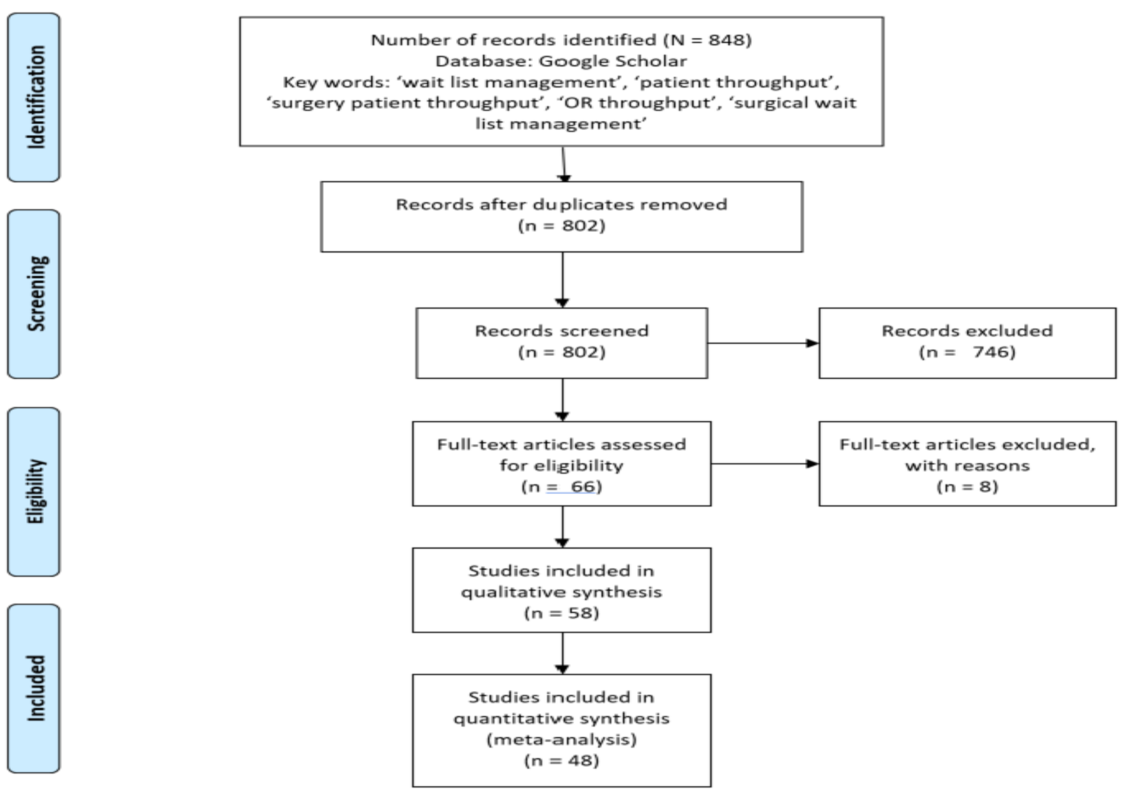

Figure 2.1: PRISMA Flow Diagram

2.2 Focus

The focus of the articles can be categorized into three main categories that include surgical scheduling, resource allocation, and review and meta-analyses. The articles associated with each category are presented in Table 2.1. There were fifteen articles identified related to surgical scheduling, seven articles related to resource allocation, and four articles identified as literature reviews. The remaining articles were not easily grouped into the specified categories. Table 2.1 categorized the articles based on the focus of the articles. Each of these categories are described below in detail.

Table 2.1: Summary of the Focus of the Articles

Focus	
Review	(Cardoen et al., 2010; Saleh, Novicoff, Rion, MacCracken, & Siegrist, 2009; Sobolev, Sanchez, & Vasilakis, 2011)
Surgical Scheduling	(Astaraky & Patrick, 2015; Banditori, Cappanera, & Visintin, 2013; Everett, 2002; Fügener, Hans, Kolisch, Kortbeek, & Vanberkel, 2014; Lamiri et al., 2009; Noyan Ogulata & Erol, 2003; Saadouli, Jerbi, Dammak, Masmoudi, & Bouaziz, 2014; Santibáñez, Begen, & Atkins, 2007; P. T. Vanberkel et al., 2011; Vasilakis, Sobolev, Kuramoto, & Levy, 2007; S. Wang, Roshanaei, Aleman, & Urbach, 2016; J. Zhang, Dridi, & Moudni, 2019; Z. Zhang & Xie, 2015)
Resource Allocation	(Dayarathna, Mismesh, Nagahisarchoghaei, & Alhumoud, 2020; Landa, Tànfani, & Testi, 2013; Lin, Sir, & Pasupathy, 2013; Niu, Peng, & ElMekkawy, 2013; Ozcan, Tànfani, & Testi, 2017; Vanberkel & Blake, 2007; Vansteenkiste et al., 2012)

2.2.1 Review

Manuscripts pertaining to operating room planning and scheduling were reviewed by Cardoen et al. (2010). It was identified that many papers analyze the elective surgical patients but do not analyze include emergency patients despite the impact the uncertainty of emergency patients have on standard scheduling techniques. Further, it was observed that many articles did not specify the type of patient the schedule was developed for in the articles. The lack of scope outlined in the articles is a large shortcoming of the previous research as it does not provide insight into the level of uncertainty present in the model as well as the transferability of the research. Additionally, the scope of many research projects is limited to a single medical site and not spread over multiple sites. “In 1997, Blake and Carter indicated in their literature review that techniques for integrating operating room scheduling with other hospital operations were urgently required.” (Cardoen et al., 2010) This was not evident in the research that was conducted since 1997 as the majority of the articles limited the research to the operating room alone. It is recognized by Cardoen et al. (2010) that much of the limited research conducted in these areas may be due to the inherent complexity that accompanies these areas of research.

Sobolev et al. (2011) conducted a review of the use of simulation in modelling patient flow in surgical care. Four areas of the presented research were discussed: details of the simulation approach, utility for analysis of surgical care, different conclusions based on approach, and models developed specifically for healthcare. The details of the simulation approach provided in each study varied widely. The percentage of studies that described the assumptions, requirements, and input and output data were 91%, 88%, and 91%, respectively. “[T]he majority of publications (31 [91%]) provided some discussion on the utility of simulation for analyzing changes in the delivery of surgical care…”(Sobolev et al., 2011) With respect to both the details of the simulation approach, and the utility of the simulation, waitlist management was only discussed 21% of the time. Lastly, few articles discussed the involvement of policy personnel in the development of the simulation to address the needs of policy makers. It is suggested that due to variation in the presentation of the information, guidelines should be developed to aid in the “…reporting of simulation base policy analyses.” (Sobolev et al., 2011)

Saleh et al. (2009) reviewed strategies for improvement of operating room throughput for orthopedic surgery. The strategies for improving throughput in operating rooms were categorized into three areas perioperative, intraoperative, and postoperative. Perioperative intervention strategies were identified in six studies, common to four articles was parallel anesthesia induction. Intraoperative intervention strategies were identified in seven articles. Two of the articles included implementing clinical pathways one for total knee arthroplasty and one for head and neck surgical procedures. Further, one of the articles discussed the “application of linear programming models to reallocate operating room time amongst surgeons.”(Saleh et al., 2009) The postoperative intervention strategies included four articles two of which used computer simulation to model patient flow. It was identified that most of the articles evaluated the streamlining of the traditional surgical patient flow by maximizing capacity and reducing labor costs. A multidisciplinary approach toward improvement is required as multiple individual strategies culminate to increase operating room throughput.

2.2.2 Surgical Scheduling

Surgical scheduling is related to allocating cases and specialties to operating room time within a hospital for a given planning horizon. The planning horizon is not always specified but can range from as small as one week (Noyan Ogulata & Erol, 2003; Saadouli et al., 2014) to as long as 26 weeks (S. Wang et al., 2016). Everett (2002) performed a simulation to schedule patients by removing patients from the waitlist over a 1001 day time period. The analysis of the surgical schedule by J. Zhang, Dridi, & Moudni (2019) was completed whilst also considering the next planning horizon. This was done to ensure that the optimal scheduling of the current planning horizon did not negatively impact the subsequent planning horizon. The scheduling of patients was allocated to pre-determined time slots in three articles (Astaraky & Patrick, 2015; Lamiri et al., 2009; Vasilakis et al., 2007).

It was noted by Cardoen et al. (2010) that few surgical planning studies are conducted over multiple sites. Two articles that are exceptions to this developed master surgical schedules for multiple hospitals (Roshanaei, Luong, Aleman, & Urbach, 2016; S. Wang et al., 2016). The patients are grouped into categories of long, medium or short for the surgery length or length of stay to allow for some stochasticity to be incorporated into optimization models (Banditori et al., 2013; Noyan Ogulata & Erol, 2003). Further, the length of stay and recovery distributions were simplified to a single value when analyzing a single surgical specialty by J. Zhang, Dridi, & Moudni (2019). Although it was emphasized by Cardoen et al. (2010) that more surgical scheduling research needed to incorporate other areas of the hospital when developing surgical schedules, only some of the articles discussed the impacts of the recovery beds on the surgical schedule. Astaraky & Patrick (2015) scheduled patients into a pre-determined master schedule incorporating the stochastic nature of both surgical and recovery times. Everett (2002) incorporates the simplified measure of bed days by assuming it follows a normal distribution. There was little to no consideration for the interaction between the surgical schedule and the bed use in six of the articles (Banditori et al., 2013; Lamiri et al., 2009; Noyan Ogulata & Erol, 2003; Roshanaei et al., 2016; Saadouli et al., 2014; Z. Zhang & Xie, 2015).

2.2.3 Resource Allocation

Resource allocation was mainly focused on operating rooms and beds. Beds are often used as a proxy for the staff and equipment needed with the beds – this proxy implies that the beds considered in the model are staffed beds and are adequately staffed by hospital personnel (Vanberkel et al., 2011). The allocation of the operating rooms was the sole focus of the research by Vansteenkiste et al. (2012). Niu et al. (2013) considered the optimum configuration of resources for the operating room whilst considering the waiting room chairs, PACU beds, operating rooms, inpatient and outpatient beds resources available. Similarly, Lin et al. (2013) determined the optimal operating room resource levels available in the surgical services including pre-operative beds, holding nurses, anesthetists, and circulating nurses. Landa, Sonnessa, Tànfani, & Testi (2018) and Vanberkel et al. (2011) focus on the redistribution of recovery beds for surgical services. Finally, Ozcan et al. (2017) focuses on allocating beds and operating room blocks to achieve better performance of competing processes.

2.3 Metrics

The performance metrics used for analyzing interventions can be broadly categorized into four categories. The metrics include patient throughput, patient wait time, resource utilization, and cost. Increasing the throughput of the patients often leads to increases in resource utilization and decrease in patient wait time and cost. Many articles use multiple metrics to evaluate the performance of the research. Table 2.2 categorizes the metrics used in the identified articles.

Table 2.2: Summary of the Metrics of the Articles

Metrics	
Patient Throughput	(Banditori et al., 2013; Dayarathna et al., 2020; Komashie, Mousavi, & Gore, 2008; Niu et al., 2013; Santibáñez et al., 2007; Vanberkel & Blake, 2007; S. Wang et al., 2016)
Patient Wait time	(Astaraky & Patrick, 2015; Noyan Ogulata & Erol, 2003; Vanberkel & Blake, 2007; J. Zhang, Dridi, & El Moudni, 2019)
Resource Utilization	(Astaraky & Patrick, 2015; Komashie et al., 2008; Moosavi & Ebrahimnejad, 2018; Noyan Ogulata & Erol, 2003; Ozcan et al.,

Metrics	
	2017; Roshanaei et al., 2016; Vanberkel et al., 2011; Vansteenkiste et al., 2012; S. Wang et al., 2016)
Cost	(Lamiri et al., 2009; Stahl et al., 2006; S. Wang et al., 2016; J. Zhang, Dridi, & El Moudni, 2019; J. Zhang, Dridi, & Moudni, 2019; Z. Zhang & Xie, 2015)

2.3.1 Patient Throughput

Komashie et al. (2008) defines throughput as "… the amount of work that has been through the system in a period of time." The use of throughput as a metric in the surgical context focuses on increasing the work (i.e. the patient throughput) through the surgical system. Komashie et al. (2008) focused on the time required for patients to move through the system by altering the case-mix levels. It was identified that removing outpatient cases reduced throughput by 23.3%. Wang et al. (2016) and Banditori et al. (2013) developed a surgical schedule to increase throughput in the surgical department. Banditori et al. (2013) accounted for the surgical due dates of the cases in the surgical schedule maximize throughput. Wang et al. (2016) compared the patient throughput of the status quo operating room schedule and the distributed operating room schedule to illustrate the impact of accounting for the stochastic nature of patient throughput. Dayarathna et al. (2020), Niu et al. (2013), Santibáñez et al. (2007), and Vanberkel & Blake (2007) analyzed the resource allocation levels to maximize patient throughput. Dayarathna et al. (2020) improved patient throughput at a clinic by increasing the number of laboratory technicians available. Niu et al. (2013) and Santibáñez et al. (2007) aimed to maximize the throughput of patients to reduce the waiting time by determining the best distribution of resources. Santibáñez et al. (2007) categorized the patient waitlists by length for each surgical specialty and assigned weights based on the categories. Vanberkel & Blake (2007) aimed to maximize the throughput with the current resources available as well as quantifying the impact of adding and removing resources.

2.3.2 Patient Wait time

The patient wait time is the time patients wait for their surgery (also sometimes referred to as access time). The goal is to minimize the amount of time patients spend on the waitlist. Niu et al. (2013) applied weights to patients of low, medium, and high priority levels to minimize the patient wait times. Similarly, J. Zhang, Dridi, & El Moudni (2019) shortened the wait time of patient by developing a method to sort and prioritize patients based on the waiting time of patients. Astaraky & Patrick (2015) used the recommended wait time targets of patients in each priority class to minimize the wait time. The wait time is classified as the cost of booking patients past the medically recommended wait time targets. Vanberkel & Blake (2007) identified that wait times are sensitive to changes in operating room and bed resources with the bed resources impacting patient wait time more than the operating room in their case study.

2.3.3 Resource Utilization

Resource utilization was mainly focused on bed and operating room utilization. The definition of utilization is an important factor when using this metric. Vansteenkiste et al. (2012) defined utilization as capacity use expressed in time. An associated capacity use factor was identified as the percentage of time allocated for programming during the day that was used by cases. The equation used was the sum of the operating room usage divided by the sum of the total capacity available. The turnaround time was not accounted for which made achieving 100% utilization impossible. The goal is to optimally distribute capacity by evaluating the relative over capacity and under capacity use of the operating rooms. Roshanaei et al. (2016) computed the operating room utilization by dividing the mean number of open operating rooms by the total number of operating rooms available. Y. Wang et al. (2016) computed operating room utilization as the total time used for elective surgery excluding turnover time and waiting time for downstream units divided by the total operating room time assigned to elective surgery. Komashie et al. (2008) used the utilization of operating rooms as an indicator of how well the available resources were being used when altering the case-mix levels. Moosavi & Ebrahimnejad (2018) focused on the bed and operating room utilization. The second objective of the multi-objective model was to minimize the cost of extra beds acquired in the ward. The third objective aimed to minimize the idleness and overtime of the operating rooms. Astaraky & Patrick (2015) focused on the cost associated with bed utilization as it was identified that ignoring bed utilization during scheduling could be detrimental to the utilization of the resources. The ward utilization was a main focus of the development of the operating room schedule for Vanberkel et al. (2011). Ozcan et al. (2017) focused on the optimal utilization of both operating rooms and bed utilization and Noyan Ogulata & Erol (2003) focused on maximizing the operating room utilization.

2.3.4 Cost

In a hospital the operating room "…constitute the largest cost center, and consume a large proportion of total expenses." (Lamiri et al., 2009) The importance of cost to the hospital administrators when evaluating the efficacy of interventions is exemplified by Saadouli et al. (2014); ""The efficiency of the suggested solution is then validated by an illustrative example which shows that a substantial amount of operations and hence cost can be saved." (Saadouli et al., 2014) The objective of Lamiri et al. (2009) was to minimize the projected overtime costs and patient related costs but did not consider the under-utilization costs. J. Zhang, Dridi, & Moudni (2019) and Z. Zhang & Xie (2015) aimed to reduce the total costs. J. Zhang, Dridi, & Moudni (2019) minimized the total incurred cost from surgeon waiting time, operating room overtime, and operating room idling time. Whereas, Z. Zhang & Xie (2015) reduced the total costs by minimizing the cost of unscheduled patients and incurred by patients waiting; the costs were proportionate to patient priority. Stahl et al. (2006) and S. Wang et al. (2016) performed cost effectiveness studies. Stahl et al. (2006) modified process costing methods to estimate costs as defined as the total costs of patient care from admission to the preoperative preparation unit through to discharge from the post anesthesia care unit. The objective of S. Wang et al. (2016) was to minimize the costs of opening surgical suites and operating rooms, waiting cost of patients scheduled for the current planning horizon, and those deferred to the next planning horizon. The net measure of effect for the cost-effectiveness analysis was the estimated maximum number of patients treatable per day.

2.4 Methodology

The methodology used varied amongst the articles selected. The main categories included simulation, mathematical programming, and simulation optimization. Within each category there were a variety of techniques that were applied. Table 2.3 categorized the articles based on methodology.

Table 2.3: Summary of Methodology Used in the Articles

Methodology		
Simulation		
Discrete Event Simulation	(Cardoen & Demeulemeester, 2008; Everett, 2002; Komashie et al., 2008; Vanberkel & Blake, 2007; Vasilakis et al., 2007)	
Mathematical Programming		
Mixed Integer Program	(Moosavi & Ebrahimnejad, 2018; Noyan Ogulata & Erol, 2003; Santibáñez et al., 2007)	
Markov Decision Process & Approximate Dynamic Programming	(Astaraky & Patrick, 2015; J. Zhang, Dridi, & Moudni, 2019)	
Other	(Roshanaei et al., 2016; P. T. Vanberkel et al., 2011; Vansteenkiste et al., 2012; J. Zhang, Dridi, & El Moudni, 2019)	
Simulation Optimization		
Mixed Integer Program	*Discrete Event Simulation*	(Banditori et al., 2013; Neyshabouri & Berg, 2017; S. Wang et al., 2016)
	Monte Carlo	(Lamiri et al., 2009)
Other Combination	(Lin et al., 2013; Ozcan et al., 2017)	

2.4.1 Simulation

Discrete event simulation modelling can model the resource interactions of clinical pathways whilst incorporating the stochastic nature of the healthcare environment. This is often used in place of queueing theory due to the complex nature of the healthcare environment (Vanberkel & Blake, 2007). There are a variety of tools available for completing the simulation analysis including FlexSim, Arena, Extend, C++, Statecharts, and Witness. The use of simulation specific software such as FlexSim and Arena aids the credibility of the model as the visual aids "… facilitates the transmission of insights to the hospital management." (Cardoen & Demeulemeester, 2008) Simulation does not provide an optimal solution but instead determines the best range of proposed solutions. Through this, simulation "…enable informed debate between the stakeholders about the optimal solution." (Everett, 2002) Vasilakis et al. (2007) utilized simulation to compare two wait list management strategies to illustrate the advantages of each system to inform the stakeholders in their decision process. Despite the acknowledgement of the complexity of the healthcare system in some articles simplifications were made in the simulation design. Komashie et al. (2008) and Vasilakis et al. (2007) did not incorporate the recovery beds in the simulation model as the simulation model was not concerned with all surgical related activities. Further, Everett (2002) assumed normal distributions for both the length of stay and surgery duration for newly generated patients. The majority of the articles fitted distributions using goodness of fit tests to model the length of stay and surgery lengths for patients (Cardoen & Demeulemeester, 2008; Komashie et al., 2008; Vanberkel & Blake, 2007). The majority of the articles also evaluate the elective and non-elective patients to ensure the impacts of cancellations and emergency surgeries are considered in the results (Cardoen & Demeulemeester, 2008; Komashie et al., 2008; Vanberkel & Blake, 2007; Vasilakis et al., 2007) However, Everett (2002) does not consider emergency patients only urgent patients who are elective patients with the highest priority. The priority of patients in the queue was modelled by Vanberkel & Blake (2007); “using a priority scheme which incorporated observed wait time in each category for each surgeon, the lower the weight the higher the priority.” (Vanberkel & Blake, 2007) Additionally, Everett (2002) calculates the priority index of each patient at the end of each day to allow the queue to be resorted based on the updated priority of the patients. The priority of the patients was not outlined by Cardoen & Demeulemeester (2008) or Komashie et al. (2008).

2.4.2 Mathematical Programming

Mathematical programming is another popular tool to analyze surgery scheduling and planning. The use of mixed integer programming can include multiple objectives. Moosavi & Ebrahimnejad (2018) used three objective functions to study the upstream and downstream units of a surgical department. The three objective functions aimed to minimize the number of deferred patients, waiting cost of scheduled patients, idleness of overtime of operating rooms, lateness in operating on children and earliness on operating patients far from hospital. Noyan Ogulata & Erol (2003) uses a hierarchical multiple criteria mathematical programming model to develop a weekly schedule for the operating rooms. The objective is to maximize “… utilization of the total operating room capacity, balanced distribution of operations among surgical groups in terms of operation lengths and operation days, and minimization of weighted patient waiting times.” (Noyan Ogulata & Erol, 2003) The model was solved in three stages. The first stage removes the patients from the waiting list to schedule them, the second stage assigns the patients to resources, and the third stage assigns the patients to an operating room and time.

Santibáñez et al. developed a multiple objective model to "[m]inimize the sum of maximum usage of post-surgical resources pre-hospital, maximize total throughput of patients, maximize total weighted throughput of patient, minimize the sum of under throughput, minimize the sum of percentage under throughput." (2007) The objective functions are not meant to be used simultaneously but allow the user to select which objective function best suits the results required. The main decision of the model is to determine which periods and operating rooms should be assigned to each surgical specialty.

There are other mathematical models that have been used to schedule and plan surgical settings. J. Zhang, Dridi, & El Moudni (2019) used a markov decision process to develop a surgical schedule which accounted for the stochastic environment for a single elective surgery specialty with limited resources including operating rooms and surgical intensive care units. The model is designed as a two level optimzation model. The first level is related to wait list management to "…minimize the discounted estimated cost over the infinite planning horizon" (J. Zhang, Dridi, & El Moudni, 2019) and the second level is the patient assignment to a specific surgical block. Roshanaei et al. (2016) developed a large scale location allocation integer program using logic based Benders decomposition. The program was applied to the distributed operating room scheduling problem. The distributed operating room schedule "…is a centralized multi-hospital priority-based approach to elective surgery scheduling…"(Roshanaei et al., 2016) The objective is to minimize the costs of the operating rooms, the cost of patients on the waitlist who remain on the waitlist after each schedule is developed, and the cost of scheduling patients during the planning horizon. Vanberkel et al. (2011) developed a probability function to determine the probability for each surgical specialty. The probabilties are specific for each surgical specialty and each day after the surgery is completed to determine the allocation of patients to surgical blocks to ensure the inpatient wards can accommodate the patients. Lastly, Vansteenkiste et al. (2012) developed a due time model. The model focused on the capacity use of the operating rooms. The performance of the utilization was considered with three additional measures: wait time of the surgeons, ratio of the surgeons estimated time to the actual time spent for the case, and capacity usage factor. The measures were weighted, and each discipline was scored.

Astaraky & Patrick (2015), Lamiri et al. (2009), and J. Zhang, Dridi, & Moudni (2019) used simulation to find a solution to an optimization model. Astaraky & Patrick (2015) used a markov decision process model to schedule patients into a schedule to minimize the combination of patient lead time, operating room overtime, and over occupancy in the recovery beds. The markov decision process was too complex to solve using standard methods. A simulation approximate dynamic programming model was developed to solve the markov decision process model. Lamiri et al. (2009) developed a mixed integer program using monte carlo simulation to solve the model. The objective was to assign elective patients to different periods to minimize the cost of the assignment and the expected overtime. J. Zhang, Dridi, & Moudni (2019) developed a markov decision process and used an approximate dynamic programming which incorporated monte carlo simulation to solve the model. The model minimized the total cost by selecting patients to be treated on a weekly basis. The solution incorporates the uncertainty of the surgery durations and the length of stay.

2.4.3 Simulation Optimization

Simulation optimization facilitates finding the optimal solution whilst incorporating the stochastic nature of the healthcare system in the simulation. There are multiple methods to use simulation optimization that includes testing the robustness of an optimal solution, solve the optimization problem, find the optimal solution using an iterative approach, and optimize a simulation solution. Banditori et al. (2013) developed an optimal solution and identified the robustness of the solution using metrics of a cancellation and overtime threshold in a simulation model. The optimization model maximized the operating room utilization through assigning specialties to each operating room in a specific time slot within the specified planning horizon. The penalties resulting from missing due dates and bed mismatches were minimized. The solutions that were produced from the optimization model were processed through the simulation model. Neyshabouri & Berg (2017) used a similar method of simulation optimization as Banditori et al. (2013). A two stage optimization model was developed and the results were tested using a simulation model. The model aimed to plan for surgery and downstream capacity under uncertainty. The objective of the optimization model was to minimize the total costs; cost of assigning patients to surgery blocks, overtime cost for performing surgeries, and cost of lack of surgical intensive care unit (SICU) capacity. The first stage assigns patients to surgery blocks and the second stage minimizes the overtime and denied SICU admission costs. The simulation tests the optimization solution using length of stays that were uniformly distributed. S. Wang et al. (2016) compared the performance of a distributed operating room scheduling optimization model to a discrete event simulation model of the status quo surgical schedules to quantify the improvement gained through the distributed operating room schedule.

Lin et al. (2013) uses simulation optimization iteratively to identify the optimal resource level for the simulation model. The genetic algorithm generates feasible design points to specify the design of the simulation experiment. The performance measures of the simulation experiments and the relative efficiencies of the design points generated by the genetic algorithm are analyzed by the data envelopment analysis to determine the next sample point. Ozcan et al. (2017) uses simulation optimization to optimize a simulation in Witness using the built-in optimization software. "The aim is to explore and improve the results based on selected values of defined performance measures. One cannot assure that optimality is reached; however, based on various trials (scenarios), it can be determined whether the obtained solution is preferable to previous solutions." (Ozcan et al., 2017) The goal is to find resource configurations that improve the performance of the operating department. A discrete event simulation model uses priority scores of the patient. The priority scores increase each day based on a percentage of the maximum time before treatment that has elapsed. The operating time is modelled using lognormal distributions and the length of stay was modelled as normal distributions.

2.5 COVID-19 Surgery

Additional articles were investigated using the key words "COVID-19 Surgery" to determine the surgical scheduling and capacity planning work conducted on the surgery backlog created by COVID-19. Although the key words returned many results, most articles were not applicable to the research topic presented. The articles mainly focused on providing guidelines and recommendations for performing surgeries during the COVID-19 pandemic. Diaz, Sarac, Schoenbrunner, Janis, & Pawlik (2020) reviewed the recommendations from various sources to provide consolidated guidelines for performing elective surgeries during the COVID-19 pandemic. Another area of focus was identifying the surgical backlog and providing recommendations on strategies to inform the stakeholders of the factors that will need to be considered when COVID-19 is at a manageable level. American College of Surgeons, American Society of Anesthesiologists, Association of periOperative Registered Nurses, & American Hospital Association (2020) released a joint statement detailing a roadmap to resuming elective surgical procedures following the COVID-19 pandemic. Lastly, some articles focused on estimating the backlog created by COVID-19 and the length of time to eliminate the patients postponed on the waitlist. J. Wang et al. evaluated historical data relating to surgical operations in Ontario, Canada to develop “time series forecasting, queuing models, and probabilistic sensitivity analysis to estimate the size of the backlog.” (2020) The length of time and the resources required to clear the backlog created by COVID-19 were estimated. The estimated time to clear the backlog created was 84 weeks with a confidence interval of 46 - 145 weeks. Jain, Jain, & Aggarwal (2020) developed a Monte Carlo stochastic simulation to forecast the patient volume created by the cancellations of elective procedures. It is recognized there was “…no validated historical data to help predict how quickly and to what degree the health care system capacity will recover.” (Jain et al., 2020) It was predicted that, optimistically, it will take seven months for the healthcare system to perform 90% of the delayed surgeries. Pessimistically it will take 16 months to achieve the same result.

Anderson, Edward G., Freeman, Richard, Joglekar (2020) developed a computer simulation to analyze the potential ramp-up scenarios at a mid-size hospital. The model was developed using Vensim to analyze the flow dynamics of the system. The analysis was performed on a hospital that cancelled most elective surgery procedures during COVID-19. The conclusions related to ramp up suggest a huge increase in short term surgical capacity is required given there are no bed constraints. However, with the presence of bed constraints the addition of surgical services will not increase the throughput of patients. The recommendations made include allowing 20 hours of overtime per week, hire a temporary workforce to avoid overtime/burnout issues, and divert to ambulatory surgery centers to reduce impact on bed constraints. It is recognized a mix of the recommendations will facilitate an effective strategy to address the backlog of surgical patients.

2.6 Summary

The literature review provided an overview of previous research conducted regarding both patient throughput and elective surgeries during COVID-19. Cardoen et al. (2010) identified a lack of downstream consideration when developing planning and scheduling strategies. The integration of the downstream units was prevalent in the reviewed articles; however, it was not always incorporated. The reviewed articles identified most of the research focused on developing surgical schedules. There was a lack of articles which focused on the allocation of surgical resources to aid in surgical scheduling and capacity planning. The utilization of the resources was a prevalent metric of assessing the performance of the developed models. However, patient throughput was not as prevalent a metric. Additionally, although the patient throughput and the wait list length are correlated, the length of the wait list was not used as a metric in the reviewed articles. There was generally an even distribution of articles that used the simulation, mathematical programming, and simulation optimization approaches. Within simulation the most prevalent model was discrete event simulation. Table 2.4 displays a summary count of the articles with respect to the methods and corresponding metrics used. Discrete event simulation utilized throughput, wait time, and resource utilization as a metric. The patient throughput was used by two of the articles and the wait time and utilization was used by one article each. Mathematical programming models often used multiple objectives with multiple metrics to evaluate the solutions. The most prevalent one was resource utilization with seven articles, wait time and cost were each used by three articles, and patient throughput was used by one article. Simulation-optimization used throughput and resource utilization as metrics. Since simulation-optimization is a combination of the simulation and mathematical programming categories this is unsurprising as patient throughput was the most prevalent metric for simulation models and resource utilization was the most prevalent metric from mathematical programming models. Further, the initial methodology used to evaluate the surgical ramp up following COVID-19 was a computer simulation. The research presented in this thesis uses simulation to address the surgical waitlist through using patient throughput and wait list length as a metric whilst incorporating the bed and operating room resources.

Table 2.4: Metric and Method Summary Table

		Metric			
		Throughput	Wait Time	Utilization	Cost
Method	Discrete Event Simulation	2	1	1	
	Mathematical Programming	1	3	7	3
	Simulation Optimization	2		1	

3 Descriptive Analytics

The data analysis informed the model development and provided the model inputs. The collection method and the types of data provided are described in this section. The types of data analyzed include the operating room usage, patient throughput, patient waitlists, and new case attributes. The methods used to analyze each component of the data is described below.

The data for this research was collected by Nova Scotia Health (NSH) throughout the province of Nova Scotia for each quarter from January 2018 until June 2020. The datasets were created by joining multiple datasets on the unique identifier for each surgery case. The data comes from three databases including the Patient Access Registry Nova Scotia (PAR-NS), Discharge Abstract Database (DAD), and the National Ambulatory Care Reporting System (NACRS). PAR-NS provided information for the New Cases, Waitlist, and Completed Cases datasets. DAD and NACRS provided information for the Complete Cases dataset. Each row in the datasets represents a different surgery instance. The cases can be connected across each database by a unique identifier for each surgical request. Each patient is identified by an encrypted health card number. Each column in the datasets provides information specific to the surgery instance. The data fields used in the data analysis included: scheduled, status, day, week, month, year, provincial procedure code, zone, facility, fiscal quarter, specialty, priority, and completion date.

The New Cases described the cases that entered the system during a quarter. If they do not receive surgery in that quarter they become Waitlisted patients in the subsequent quarter. After surgery they become Completed Cases. The Waitlist dataset includes all cases waiting for surgery during that quarter. The Completed Cases included the cases that were completed during the quarter. These three data sets were combined to define the state of the system in any quarter.

3.1 Surgical Resources in the Central Zone

The data provided was for all surgical procedures in Nova Scotia serviced by NSH. The analyzed data focused on the Central Zone. The Central Zone services the capital city in Nova Scotia which is home to approximately 50% of the population of Nova Scotia (Statistics Canada, 2019). Within the Central Zone there are five locations at which surgeries occur; four of the locations are hospitals and one is a private clinic. The private clinic, Scotia Surgery Inc. (SSI), is contracted by NSH to perform specific outpatient surgeries. The four hospitals are Victoria General Hospital (VG), Halifax Infirmary (HI), Dartmouth General Hospital (DGH), and Hants County Hospital (HCH). The operating rooms associated with each hospital is presented in Table 3.1.

Table 3.1: Operating Rooms for Hospitals in the Central Zone

	Hospital				
	Victoria General Hospital	Halifax Infirmary	Dartmouth General Hospital	Hants County Hospital	Scotia Surgery Inc.
Operating Rooms	OPDS-17	HIOR01	DOR-RM1	HOR01	SSI01
	OPDS-18	HIOR02	DOR-RM2	HOR02	SSI02
	OPDS-19	HIOR03	DOR-RM3	RHACRMS	
	OPDS-20	HIOR04	DOR-RM4		
	VG10-09	HIOR05	DOR-RM5		
	VG10-10	HIOR06	DOR-RM6		
	VG10-11	HIOR07	DOR-RM8		
	VG10-12	HIOR08			
	VG10-13	HIOR09			
	VG10-15	HIOR10			
	VG10-16	HIOR11			
	VG11-01	HIOR12			
	VG11-03	HIOR13			
	VG11-04	HIOR14			
	VG11-05	HIOR15			
	VG11-06	HIOR16			
	VG11-07	HIOR17			
	VG11-08	HIOR18			
		HIOR19			

There are twelve surgical specialties within the department of surgery: cardiology/cardiac (CARD), general (GEN), neurology (NEURO), gynecology (OBGYN), oral maxilla facial dental (OMFD), ophthalmology (OPHTH), orthopedic (ORTHO), otolaryngology (OTOL), plastic (PLAS), thoracic (THOS), urology (URO), and vascular (VAS). Each surgical specialty has procedure codes for each procedure. The procedure codes follow a similar labelling system for all specialties; the abbreviated surgical specialty name is followed by four numbers. The number of surgical procedures for each surgical specialty are listed in Table 3.2. There are 398 surgical procedure codes in total.

Table 3.2: Number of Procedure Codes for Each Surgery Type

Surgery Type	Number of Procedure Codes
Cardiology/Cardiac (CARD)	17
General (GEN)	82
Neurology (NEURO)	36
Gynecology (OBGYN)	21
Oral Maxilla Facial (OMFD)	9
Ophthalmology (OPHTH)	20
Orthopedic (ORTHO)	67
Otolaryngology (OTOL)	42
Plastic (PLAS)	22
Thoracic (THOS)	15
Urology (URO)	52
Vascular (VAS)	14
Total Procedure Codes	398

Table 3.3 provides a summary of the Central Zone surgical facilities. The DGH has seven operating rooms and 33 surgical beds. At the DGH six surgical specialties operate including general surgery, gynecology, oral maxilla facial, orthopedic, otolaryngology, and urology. The HI has 19 operating rooms and 203 surgical beds. There are six surgical specialties including cardiology/cardiac, general, neurology, orthopedic, plastic, and vascular. The VG has 19 operating rooms and 121 surgical beds. General, gynecology, oral maxilla facial, otolaryngology, thoracic, urology, and ophthalmology are all performed at the VG. HCH and SSI perform only outpatient procedures and do not have any inpatient beds available for surgical procedures. HCH has three operating rooms to perform general, oral maxilla facial, orthopedic, otolaryngology, and vascular surgical procedures. SSI has two operating rooms and performs surgery for general, orthopedic, and plastic specialties.

Table 3.3: Central Zone Hospital Summary Table

Central Zone Surgical Facilities	Operating Rooms	Surgical Beds	Surgical Specialties
Dartmouth General Hospital	7	33	6
Halifax Infirmary	19	203	6
Victoria General Hospital	19	121	7
Hants County Hospital	3	-	7

Central Zone Surgical Facilities	Operating Rooms	Surgical Beds	Surgical Specialties
Scotia Surgery Inc	2	-	3
Total	50	357	

3.2 Operating Room Schedule and Use

The operating room schedule for each operating room was not attainable from each hospital as realized schedules are not retained electronically and the Master Schedule is followed inconsistently. The schedules for the operating rooms were therefore derived from the historical surgical use data. The average of the number of hours the operating room was used on each day of the week provides an estimate for the number of hours the operating room was available for scheduled surgeries. The times were rounded up to the nearest hour as there is a maximum of a hour buffer incorporated into the operating room schedule.

Operating rooms are used for unscheduled surgeries on the weekends and evenings or early mornings. The number of operating rooms open on the weekends was identified by counting the number of unique operating rooms used on each weekend of each month. The aid of the subject matter experts facilitated further analysis of the data. It was evident that not all operating rooms were available on the weekends with 30-40% of the operating rooms open on the weekends at each surgical facility.

Each surgical specialty has specific operating rooms in which to perform operations. Multiple surgical specialties use the same operating room. The data does specify on which days of the week the operating room is used for each surgical specialty but does not specify the time of day. An analysis of the distribution of the number of hours used by each surgical specialty on each day of the week was performed. The procedure code and surgical specialty were documented for each completed operation and the corresponding operating room that was used for the surgery. The number of hours available per specialty was captured using the percentage of the total number of hours the surgical specialty used each operating room and the total number of hours the operating room was available for use during the week. The number of hours each surgical specialty used in each operating room per week was added together to determine the total number of hours available for each surgical specialty each day of the week.

3.2.1 Operating Room use at Dartmouth General Hospital

Each of the hospitals in the Central Zone were analyzed to determine the operating room schedule, surgical specialty operating use, and emergency operating rooms. This section presents a detailed analysis of the results for DGH. The results of the other three facilitates is presented in Appendix A.

The operating room schedule at DGH is displayed in Table 3.4. Table 3.4 illustrates the number of hours each operating room is in operation during each day of the week beginning at 8:00AM. The darker the shade of read the more hours the operating room is being used during that day of the week. The operating rooms are used between 3 and 12 hours per day. Operating room DOR-RM5 is used the most, 61 hours per week, and DOR-RM6 is used the least, 7 hours, during the week on average. Further, the aggregate of the data shows the operating rooms are all used between 3 and 5 hours on the weekends for emergency surgical procedures. Table 3.5 illustrates the number of times each operating room was open on each weekend for the two year period.

Table 3.4: Dartmouth General Hospital Operating Room Schedule Data

Day	DOR-RM1	DOR-RM2	DOR-RM3	DOR-RM4	DOR-RM5	DOR-RM6	DOR-RM8
Sunday	4	4	4	3	5	0	2
Monday	10	9	11	9	9	6	7
Tuesday	9	8	9	6	12	0	3
Wednesday	9	8	7	7	11	0	6
Thursday	7	8	10	6	10	1	6
Friday	8	10	12	7	9	0	7
Saturday	4	4	5	3	5	0	3
Total	51	51	58	41	61	7	34

Table 3.5: Dartmouth General Hospital Operating Room Weekend Use

OR	2018			2019		
	Saturday	Sunday	Weekend	Saturday	Sunday	Weekend
DOR-RM4	12	11	12	12	12	12
DOR-RM3	12	11	12	12	12	12

OR	2018			2019		
	Saturday	Sunday	Weekend	Saturday	Sunday	Weekend
DOR-RM5	12	12	12	11	10	11
DOR-RM2	11	9	10	10	7	9
DOR-RM1	4	3	4	7	3	5
DOR-RM8	0	0	0	1	1	1

The amount of time used by each surgical specialty at DGH is illustrated in Table 3.6. The operating rooms are not always exclusive to each specialty but rather are shared amongst specialties. The specialty with the largest number of operating room hours at DGH is orthopedic surgery with around 95 hours per week. Orthopedic surgery is the only surgery specialty that uses DOR-RM2 and shares DOR-RM3 with oral and maxillofacial surgery. General surgery mainly uses the operating rooms DOR-RM1 and DOR-RM5 with a total number of 81 hours per week. DOR-RM6 is used by general and plastic surgery evenly.

Table 3.6: Dartmouth General Hospital Operating Room Time Distribution for Surgical Specialty

Room	GEN	OBGYN	OMFD	ORTHO	OTOL	PLAS
DOR-RM1	30.9	0.0	0.0	0.0	20.0	0.0
DOR-RM2	0.0	0.0	0.0	51.0	0.0	0.0
DOR-RM3	0.0	0.0	13.7	44.3	0.0	0.0
DOR-RM4	12.8	0.0	0.0	0.0	0.0	0.0
DOR-RM5	34.0	26.9	0.0	0.0	0.0	0.0
DOR-RM6	3.5	0.0	0.0	0.0	0.0	3.5
DOR-RM8	0.0	0.0	0.0	0.0	0.0	0.0
Total	81.3	26.9	13.7	95.3	20.0	3.5

The total number of hours allotted to each specialty for the entire Central Zone is displayed in Table 3.7. Orthopedic surgery has the largest number of operating room hours in a week at 524.7 hours. General surgery and urology have a similar number of operating room hours with 330 hours. The surgical specialty with the lowest number of hours is oral maxilla facial and dental surgery with 16.4 hours per week.

Table 3.7: Central Zone Operating Room Time Distribution per Surgical Specialty per Week

Specialty	CARD	GEN	NEURO	OBGYN	OMFD	OPHTH	ORTHO	OTOL	PLAS	THOS	URO	VAS
OR Time (hr)	178	339	158.2	49.6	16.4	202.4	547	60.2	53	48	328.2	173.5

The resulting operating room schedule used for DGH is displayed in Table 3.8.

Table 3.8: Dartmouth General Hospital Operating Room Schedule

<table>
<tr><th></th><th>Sunday</th><th>Monday</th><th>Tuesday</th><th>Wednesday</th><th>Thursday</th><th>Friday</th><th>Saturday</th></tr>
<tr><td>0:00</td><td rowspan="17">DOR-RM4
DOR-RM3
DOR-RM5</td><td rowspan="8">DOR-RM4
DOR-RM3
DOR-RM5</td><td rowspan="8">DOR-RM4
DOR-RM3
DOR-RM5</td><td rowspan="8">DOR-RM4
DOR-RM3
DOR-RM5</td><td rowspan="8">DOR-RM4
DOR-RM3
DOR-RM5</td><td rowspan="8">DOR-RM4
DOR-RM3
DOR-RM5</td><td rowspan="17">DOR-RM4
DOR-RM3
DOR-RM5</td></tr>
<tr><td>1:00</td></tr>
<tr><td>2:00</td></tr>
<tr><td>3:00</td></tr>
<tr><td>4:00</td></tr>
<tr><td>5:00</td></tr>
<tr><td>6:00</td></tr>
<tr><td>7:00</td></tr>
<tr><td>8:00</td><td rowspan="6">DOR-RM1
DOR-RM2
DOR-RM3
DOR-RM4
DOR-RM5
DOR-RM6
DOR-RM8</td><td rowspan="3">DOR-RM1
DOR-RM2
DOR-RM3
DOR-RM4
DOR-RM5
DOR-RM8</td><td rowspan="6">DOR-RM1
DOR-RM2
DOR-RM3
DOR-RM4
DOR-RM5
DOR-RM8</td><td>DOR-RM1
DOR-RM2
DOR-RM3
DOR-RM4
DOR-RM5
DOR-RM6
DOR-RM8</td><td rowspan="7">DOR-RM1
DOR-RM2
DOR-RM3
DOR-RM4
DOR-RM5
DOR-RM8</td></tr>
<tr><td>9:00</td><td rowspan="5">DOR-RM1
DOR-RM2
DOR-RM3
DOR-RM4
DOR-RM5
DOR-RM8</td></tr>
<tr><td>10:00</td></tr>
<tr><td>11:00</td><td rowspan="3">DOR-RM1
DOR-RM2
DOR-RM3
DOR-RM4
DOR-RM5</td></tr>
<tr><td>12:00</td></tr>
<tr><td>13:00</td></tr>
<tr><td>14:00</td><td>DOR-RM1
DOR-RM2
DOR-RM3
DOR-RM4
DOR-RM5
DOR-RM8</td><td rowspan="2">DOR-RM1
DOR-RM2
DOR-RM3
DOR-RM5</td><td>DOR-RM1
DOR-RM2
DOR-RM3
DOR-RM4
DOR-RM5</td><td>DOR-RM1
DOR-RM2
DOR-RM3
DOR-RM5</td></tr>
<tr><td>15:00</td><td rowspan="2">DOR-RM1
DOR-RM2
DOR-RM3
DOR-RM4
DOR-RM5</td><td>DOR-RM1
DOR-RM2
DOR-RM5</td><td>DOR-RM2
DOR-RM3
DOR-RM5</td><td>DOR-RM1
DOR-RM2
DOR-RM3
DOR-RM5</td></tr>
<tr><td>16:00</td><td>DOR-RM1
DOR-RM3
DOR-RM5</td><td>DOR-RM1
DOR-RM5</td><td>DOR-RM3
DOR-RM5</td><td>DOR-RM2
DOR-RM3
DOR-RM5</td></tr>
</table>

	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
17:00		DOR-RM1 DOR-RM3	DOR-RM5	DOR-RM5		DOR-RM2 DOR-RM3	
18:00		DOR-RM4 DOR-RM3 DOR-RM5	DOR-RM4 DOR-RM3 DOR-RM5	DOR-RM4 DOR-RM3 DOR-RM5	DOR-RM4 DOR-RM3 DOR-RM5	DOR-RM4 DOR-RM3 DOR-RM5	
19:00							
20:00							
21:00							
22:00							
23:00							

3.3 Distribution Fitting

The length of stay and the surgery length of each patient was determined using the historical data of the completed surgical cases. An empirical distribution was developed for each procedure code for both the acute length of stay in the hospital and the length of the surgery.

3.3.1 Length of Stay

A distribution for the length of stay was fit to the data for the completed surgeries stratified by procedure code. The length of stay of the patients was categorized by both the acute days and the alternate level of care days. The acute days are the days under which the patient is being cared for by a surgeon. These are the days that impact the number of surgery beds being used by surgery patients. Alternate level of care days are days during which the patients are no longer under the care of the surgery department and are considered medicine patients. Stratifying length of stay by procedure code allows different procedure codes to be modelled by different distributions.

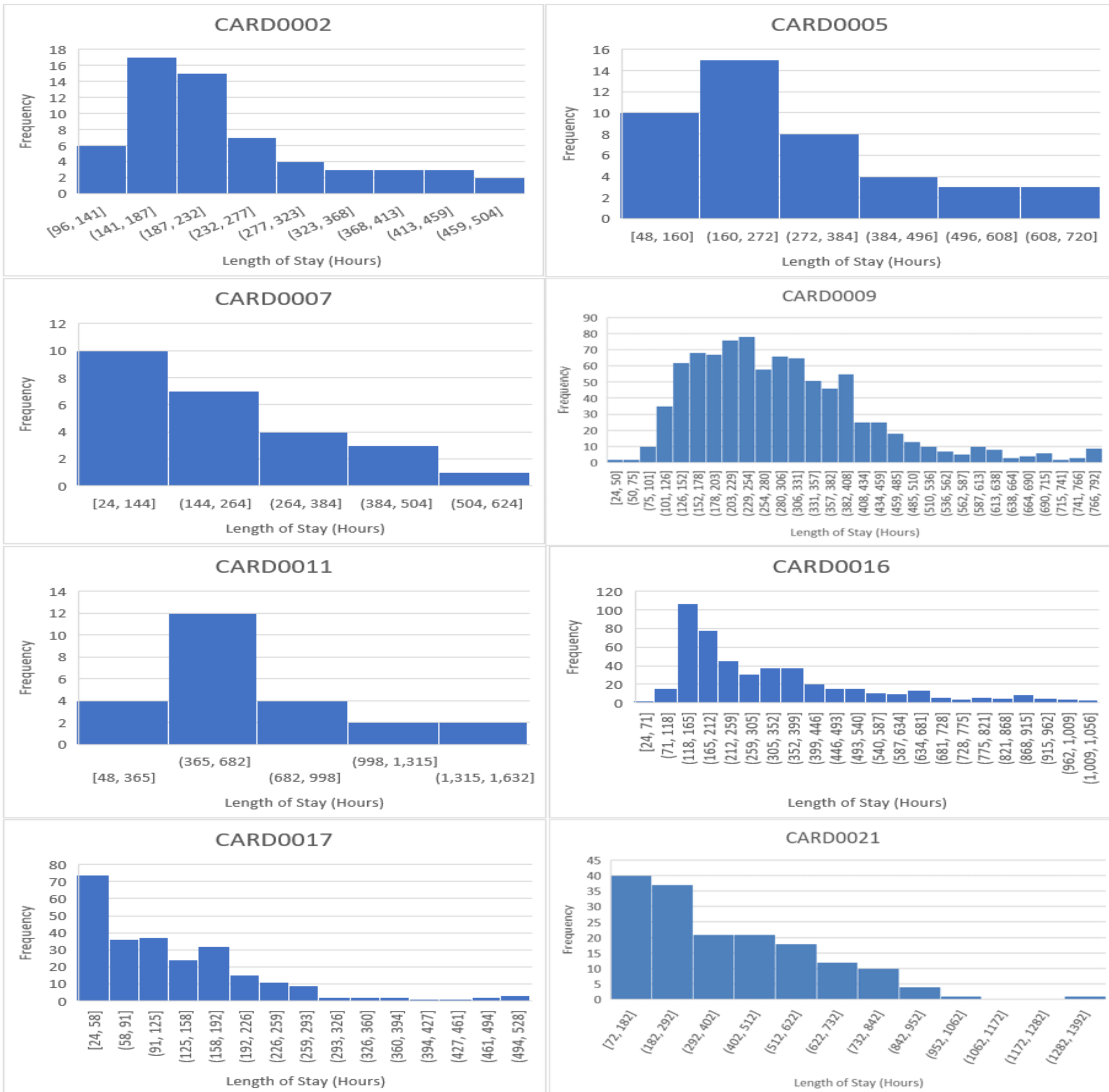

Figure 3.1: Cardiac Surgery Procedure Code Length of Stay (Hours) Histograms

The histograms and summary statistics for each procedure code were obtained to understand the characteristics of the data for each procedure code. Figure 3.1 displays the length of stay distributions for the cardiac surgery procedure codes. The number of bins in each histogram in Figure 3.1 is dependent on the number of data points. The summary statistics and histograms illustrated that the data distributions for the procedure codes are skewed to the left as the mean and median values are not similar. The skewed nature of the data warranted further investigation. The skewed data indicated that the centrality was best represented by the median. The data contained outliers that represented lengths of stays or surgery lengths that were much longer than the median. Through discussions with subject matter experts regarding the variability present in the data it was evident that outliers represent emergency patients. Emergency patients are often viewed as an administrative problem with respect to the length of stay as the patients are often being treated for multiple comorbidities. For these two reasons the 95th to 100th percentile of the data were removed before fitting distributions and computing summary statistics. The data remained skewed to the left after the removal of the top 5% but allowed for the removal of the outliers and data entry errors.

The new data set was used to determine if procedure codes should be grouped together. Procedure codes with was less than twenty data points were considered for grouping. Twenty sample data points were not enough to allow an empirical distribution to be developed. The minimum, maximum, and interquartile range of the procedure code with less than 20 data points were compared. The maximum value was used as an indicator of the length of the tail of the data. The interquartile range and the median were used to compare the range and central tendency of the data set. The smaller data set was combined with the larger data set when the interquartile range of the two data sets overlapped to include the medians of both data sets. This is evident in the grouping presented in Table 3.10. The median of both procedure codes are present in the interquartile range. Table 3.9 summarizes the procedure code groupings for all surgical specialties by categorizing the number of procedure codes that have less than two data points as well as the procedure codes with less than 20 data points and the number of groupings for the procedure codes with less than 20 data points.

Table 3.9: Length of Stay Grouping Summary

	>2 & <20	<2	Groupings
CARD	7	2	5
GEN	11	15	8
NEURO	9	6	8
OBGYN	3	5	3
OMFD	1	2	1
OPHTH	2	4	3
ORTHO	14	13	9
OTOL	4	16	3
PLAS	6	4	5

	>2 & <20	<2	Groupings
THOS	2	3	2
URO	13	9	8
VAS	2	3	2

The remaining procedure codes were not grouped together. It was identified by the subject matter experts that to ensure the integrity and credibility of the model procedure codes which possessed more than 20 data points could not be grouped together as the corresponding procedures would not, from a medical perspective, be grouped together despite the similarity of the data. Further, there were some procedure codes that only appeared once for the duration of the two years. Due to the inability to group these procedures with other procedures because the characteristics of the procedures were unknown all patients that entered the system with those procedure codes were given a surgery length or length of stay equivalent to the single data point.

The distributions were developed using a method which returned a distribution with the least residual sum of squares (RSS) between the hypothesized distribution and the sample data. The code developed to fit the data to distributions was modified from a code (tmthydvnprt, 2016).The RSS is calculated using equation (1). The sample data, y_i, is compared to the hypothesized data, $f(x_i)$, where i is the ith value in the dataset. The squared difference between the values is the error present between the sample data and the hypothesized data. The sample data was compared against a list of distributions to determine which distribution in the list best fit the data. The distributions were beta, erlang, exponential, exponentially modified normal and Weibull, exponential power, gamma, generalized gamma, inverse gamma, inverse gauss, inverse Weibull, Johnson SB, Johnson SU, Sech-squared, log gamma, log Laplace, log normal, normal, Pearson type three, triangular, truncated exponential, uniform, Weibull, and Weibull maximum and were evaluated using scipy.stats in Python (The SciPy community, 2021). The distribution with the best fit was returned as well as the necessary parameters of the distribution. This was accomplished using a Python code developed to test distributions. The program developed the distribution for each data set as well as the RSS. The program retained the RSS of the first distribution calculated and compared the next distribution RSS value to the current best value. The best value was replaced by the distribution being checked if the RSS value was less than best RSS value. The distribution associated with the new RSS value would be maintained as the best distribution until proven otherwise or until all distributions were analyzed.

$$RSS = \sum_{i=1}^{n} \left(y_i - f(x_i)\right)^2 \tag{1}$$

Table 3.10: Length of Stay CARD0002 & CARD0007 Procedure Code Summary Statistics

Procedure Code	Count (days)	Mean (days)	Std (days)	Min (days)	25% (days)	50% (days)	75% (days)	95% (days)
CARD0002	64	11.02	7.71	4	7	9	12.25	25.74
CARD0007	15	12.93	16.30	3	4.5	10	12	56.24

The analysis performed on the length of acute stay data allowed distributions to be fit for most of the surgical procedures. Table 3.10 illustrates two procedures in the cardiac surgery specialty that were grouped together. The resulting distribution for the procedure types was an inverse gaussian distribution which has one shape argument parameter as well as the location and scale parameters, 0.167, -39.784, 2011.965, respectively. The distributions used for the length of stay for each procedure codes is presented in Table 3.11. The distribution used the most was the gamma distribution and the distribution used the least was the log-normal distribution.

Table 3.11: Length of Stay Distribution Type Counts per Surgical Specialty

Distribution	CARD	GEN	NEURO	OBGYN	OMFD	OPHTH	ORTHO	OTOL	PLAS	THOS	URO	VAS	Total
Gamma	0	19	8	2	2	2	22	6	4	0	10	4	79
Log Laplace	0	7	6	2	0	0	2	1	0	6	5	1	30
Pearson Type 3	0	1	4	1	1	5	4	2	3	1	3	0	25
Beta	0	12	1	0	0	0	5	1	1	0	1	1	22
Generalized Gamma	0	7	0	2	0	1	7	0	2	0	2	1	22
Johnson SU	3	3	2	0	0	0	0	3	0	2	4	0	17
Exponential Weibull	0	2	0	2	0	1	3	1	0	1	6	0	16
Inverse Gauss	3	1	1	4	0	0	2	1	0	0	2	0	14
Weibull Min	0	5	0	0	2	1	0	5	0	0	1	0	14
Exponentially Modified Normal	7	4	0	0	0	0	1	0	0	0	0	1	13

Distribution	CARD	GEN	NEURO	OBGYN	OMFD	OPHTH	ORTHO	OTOL	PLAS	THOS	URO	VAS	Total
Exponential Power	2	3	4	0	0	0	0	0	0	1	0	0	10
Inverse Gauss	0	0	2	0	0	0	2	0	0	0	2	0	6
Inverse Weibull	0	1	3	0	0	0	1	0	0	0	0	0	5
Johnson SB	0	1	0	0	0	0	3	0	0	0	0	1	5
Triangular	0	3	0	0	0	0	0	0	0	1	0	0	4
Weibull Max	0	1	0	0	0	0	0	0	1	0	0	0	2
Log Normal	0	0	0	0	0	0	0	0	0	0	0	2	2

3.3.2 Surgery Length

A surgery length distribution was fit to the data for each procedure code. The operating room time data was recorded in segments based on different stages of the surgery. The timestamps include: setup start, patient enters, surgeon start incision, surgeon end, patient exit, finish clean up. The time between finish cleanup and setup start is used as the total time the operating room is occupied per surgery. The surgery length analysis was similar to that of the length of stay discussed previously in this section. The summary statistics for each procedure code were analyzed and it was identified that the data distributions for the procedure codes were skewed to the left as the mean and median values were not similar. The data contained outliers which represented surgery lengths that were sometimes longer than 24 hours. Subject matter experts identified that those outliers were a results of data entry error. Additionally, for some of the procedure codes the longer surgery lengths were a result of complex traumas from emergency patients which are not representative of the elective surgery patients. These 95th to 100th percentile of the data was removed to facilitate an analysis of the elective surgical patients within the system.

The grouping procedure for the data set was similar to that used for the length of stay as well. The procedure code data with the removed 95th percentile was only grouped together when the sample data for the procedure code was less than 20 data points. The interquartile range as well as the maximum value was used to determine if the data similarly described another data set. It was identified by the subject matter experts that to ensure the integrity and credibility of the model procedure codes which possessed more than 20 data points could not be grouped together as the corresponding procedures would not, from a medical perspective, be grouped together despite the similarity of the data. Further, there were some procedure codes that only appeared once for the duration of the two years. Due to the inability to group these procedures with other procedures because the characteristics of the procedures were unknown all patients that entered the system with those procedure codes were given a surgery length equivalent to the single data point. The smaller data set was combined with the larger data set when the interquartile range of the two data sets overlapped to include the medians of both data sets. This is evident in the grouping presented in Table 3.13. The median of both procedure codes are present in the interquartile range. Table 3.12 summarizes the procedure code groupings for all surgical specialties by categorizing the number of procedure codes that have less than two data points as well as the procedure codes with less than 20 data points and the number of groupings for the procedure codes with less than 20 data points.

Table 3.12: Surgery Length Grouping Summary

	<2	>2 & <20	Groupings
CARD	0	6	5
GEN	6	18	10
NEURO	9	8	6
OBGYN	3	7	7
OMFD	0	4	2
OPHTH	4	1	1
ORTHO	3	17	12
OTOL	10	9	9
PLAS	2	9	5
THOS	1	3	3
URO	3	13	11
VAS	0	3	3

Table 3.13: Surgery Length CARD0025 & CARD0012 Procedure Codes Summary Statistics

	Count (hours)	Mean (hours)	Std (hours)	Min (hours)	25% (hours)	50% (hours)	75% (hours)	Max (hours)
CARD0025	4	92	24.39	64	79	91	104	118.4
CARD0012	43	100.5	48.09	41	63	88	124	181.9

The development of the surgery length distributions used the same program that was developed for the length of stay distributions, as previously discussed in Subsection 3.3.1. Table 3.13 illustrates two procedures in the cardiac surgery specialty that were grouped together. The resulting distribution for the procedure types was a truncated exponential distribution which has one shape argument parameter as well as the location and scale parameters, 1.000, 0.683, 2.033, respectively. The count for the procedure codes for each surgical specialty for each of each type of distribution is displayed in Table 3.14. The distribution used the most was a Johnson SB distribution and the distribution used the least was log-gamma distribution.

Table 3.14: Surgery Length Distribution Counts per Surgical Specialties

Distribution	CARD	GEN	NEURO	OBGYN	OMFD	OPHTH	ORTHO	OTOL	PLAS	THOS	URO	VAS	Total
Johnson SB	2	10	2	3	4	3	9	8	3	1	9	0	54
Exponentially Modified Normal	0	11	9	1	0	2	7	7	1	2	5	3	48
Triangular	0	8	2	0	0	5	7	4	3	4	6	4	43
Log Laplace	4	12	3	2	0	1	6	0	3	2	7	1	41
Johnson SU	1	8	3	1	3	2	9	3	1	0	5	0	36
Inverse Weibull	1	9	3	2	1	0	5	1	2	0	1	0	25
Inverse Gauss	2	4	0	2	1	2	4	0	0	0	4	4	23
Beta	0	4	1	2	0	0	9	4	0	0	0	0	20
Gamma	0	0	0	0	0	1	4	4	8	1	1	0	19
Generalized Gamma	0	3	0	2	0	0	4	2	5	0	1	0	17
Exponential Power	0	3	1	1	0	2	0	0	1	0	3	2	13
Logistic	0	2	3	0	0	0	2	0	0	2	3	0	12
Inverse Gamma	2	1	0	0	0	2	0	0	3	0	0	0	8
Truncated Exponential	2	0	0	3	0	0	1	1	0	0	0	0	7
Pearson Type Three	1	0	1	0	0	0	2	2	0	1	0	0	7
Weibull Minimum	2	3	1	0	0	0	0	0	0	0	1	0	7
Exponentially Modified Weibull	0	0	0	0	0	0	0	2	0	0	3	0	5
Weibull Maximum	0	0	2	0	0	0	0	0	1	0	1	0	4
Uniform	0	0	0	0	0	0	1	0	0	1	0	0	2
Log Gamma	0	0	0	0	0	0	0	2	0	0	0	0	2

3.4 Demand and Throughput

The demand and throughput of the system are described by three components: arrival rate, service rate, and renege rate. The results from the demand and throughput data analysis are presented below which include the new, completed, and removed cases. The overall characteristics of the queue which is a result of the arrival, service and removals are illustrated in Figure 3.2. The waitlist decreases when the completed and removed cases are greater than the new cases added to the waitlist. There is an upward trend illustrated in the graph except for the first quarter of 2020 where COVID-19 halted the elective surgical procedures from being added to the waitlist as well as being completed. The first quarter of 2020 was not included in the data analysis to ensure the outlier events did not impact the trends.

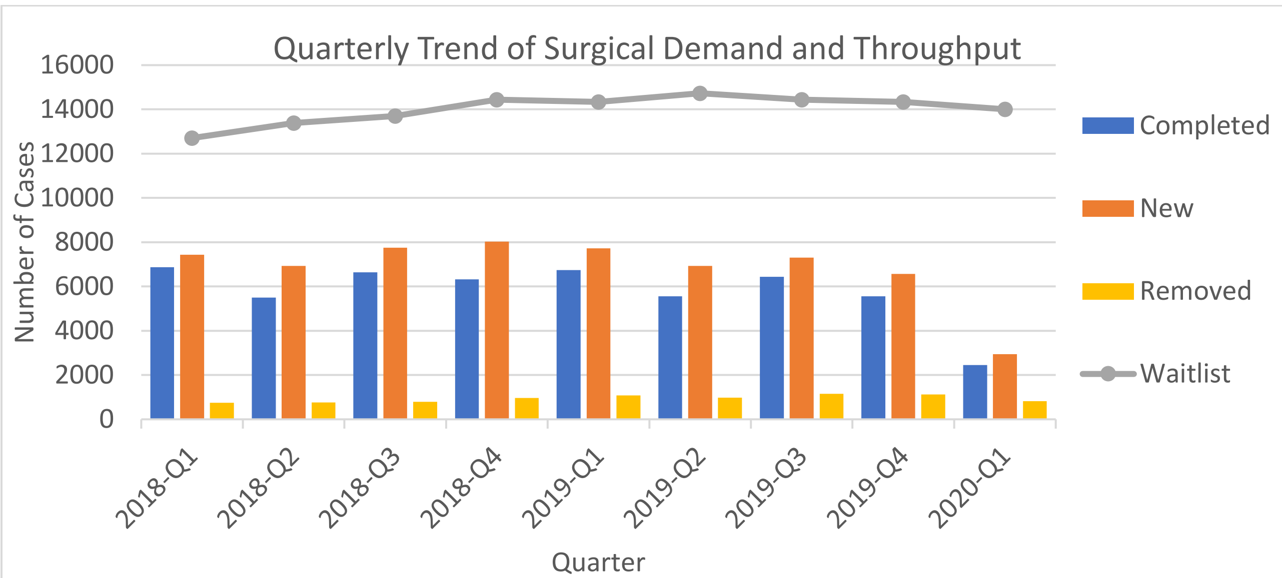

Figure 3.2: Central Zone Throughput and Demand of the Surgical Services

3.4.1 Arrival Rate

The arrival rate describes the number of arrivals to the system per unit of time. The number of arrivals to the system indicate the rate at which patients are entered onto the waitlist and emergency patients are added to the operating room queue. The arrival rate was analyzed on a yearly, quarterly, and monthly basis. The arrival rate was calculated using equation (2). The arrival rate was calculated using the new scheduled cases that arrived each year, quarter and month from January 2018 – December 2019. The data provided for 2020 was not included in the analysis to ensure the implications of COVID-19 on the demand of the system did not affect the arrival rate. The quarterly and monthly arrival rate were analyzed to determine which arrival rate most accurately described the system. It was important to investigate the seasonality of the arrival rate as it was known by subject matter experts that the arrival rate changes based on the time of year. The arrival rate on a daily and hourly basis was not evaluated as this level of detail was not necessary for the model analysis. The arrival rate facilitates the calculation of the interarrival rate of each of the patients in the model.

$$Arrival\ Rate = \frac{Number\ of\ New\ Cases}{time} \tag{2}$$

The number of new cases added to the waitlist per month from January 2018 until June 2020 is displayed in Figure 3.3. The average arrival rate per month based on two years of historical data, January 2018 – December 2019, is presented in Table 3.15. The arrival rate is around 3000 new cases per month. There is a seasonal trend present in the data. The arrival rate decreases during holiday seasons which include December, March, July, and August with the lowest arrival rate in August. The arrival rates increase following the holidays with the highest arrival rate in January. It is evident during the first wave of the COVID-19 pandemic there was a large decrease in the number of cases added to the waitlist as compared to the same time in other years.

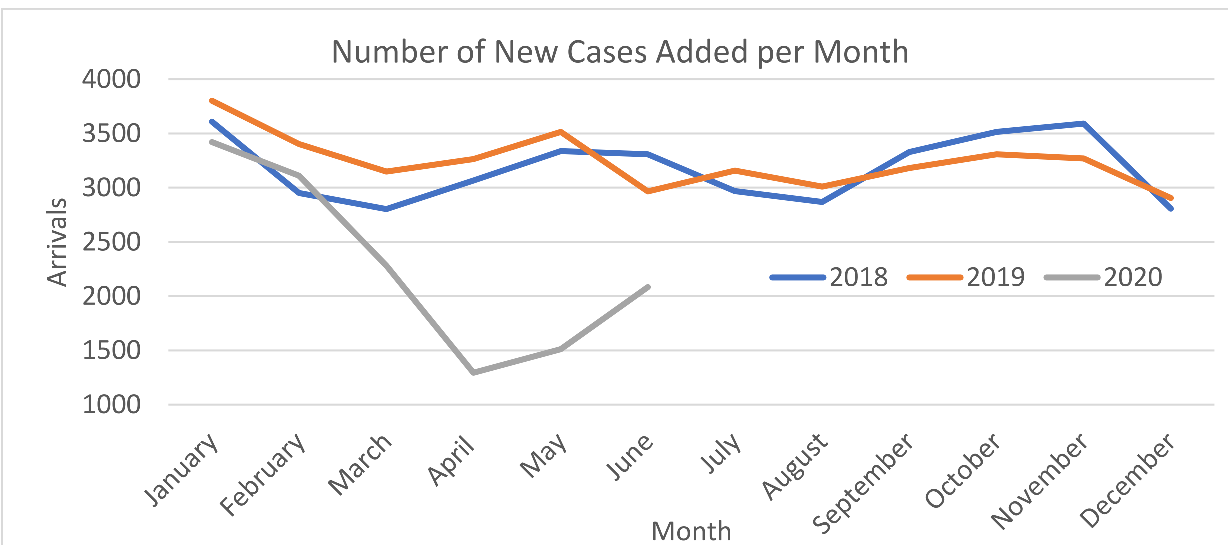

Figure 3.3: Number of New Cases Added Per Month January 2018 - June 2020 Central Zone

Table 3.15: Average Arrival Rate per Month from January 2018 – December 2019 Central Zone

Month	Arrivals Per Month
January	3,347

Month	Arrivals Per Month
February	3,176
March	2,688
April	2,954
May	3,094
June	2,928
July	2,767
August	2,654
September	3,184
October	3,081
November	3,202
December	2,580

3.4.2 Service Rate

The service rate is the rate at which patients are served by the system in a unit of time. The service rate is not used as an input to the simulation but is an important to characterize the waitlist. The service rate was further used in the model validation to ensure the service rate of the model accurately represented the system. The service rate was calculated using the Completed Cases data set. The data set indicated the number of completed cases during the two year period, January 2018 – December 2019. The service rate was calculated for a yearly, quarterly, and monthly basis. The service rate equation is:

$$Service\ Rate = \frac{Number\ of\ Completed\ Cases}{time} \tag{3}$$

The number of cases removed from the waitlist per month from January 2018 until June 2020 is displayed in Figure 3.4. The service rate per month for two years of historical data, January 2018 – December 2019, is presented in Table 3.16. The trends in the number of removed cases per month matches the trends present in the number of arrivals per month.

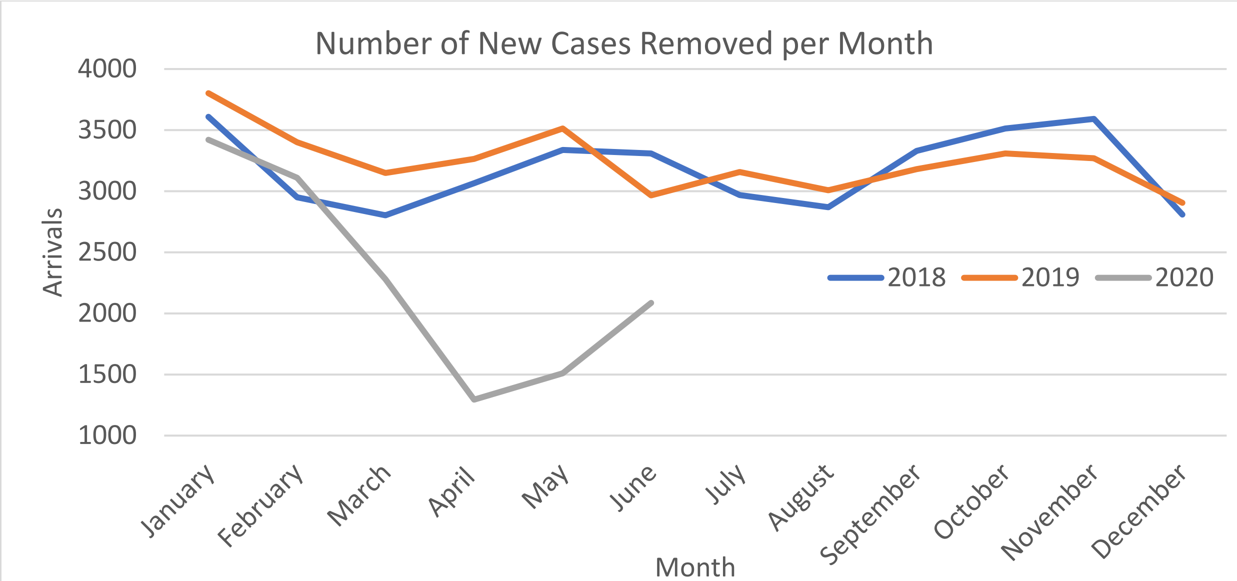

Figure 3.4: Number of Cases Removed per Month January 2018 – June 2020 Central Zone

Table 3.16: Average Service Rate Per Month January 2018 – December 2019 Central Zone

Month	Service Per Month
January	2,845
February	2,755
March	2,419
April	2,663
May	2,890
June	2,744
July	2,285
August	2,086
September	2,946
October	2,850
November	2,822
December	2,310

3.4.3 Renege Percentage

The renege percentage is the number of cases that are removed from the waitlist without receiving surgery. The renege percentage was used as a patient attribute in the simulation model. Through discussions with subject matter experts, it was identified that the renege rate within NSH is 14% across the province for the entire surgical waitlist. The renege percentage was calculated for each surgical specialty using the number of patients on the waitlist at the start of the quarter, the waitlist at the end of the quarter, the number of completed cases, and the number of new cases. The removed cases were calculated using equation (3). The renege percentage was then calculated using equation (4). The quarters were evaluated to determine the percentage of patients that are initially on the waitlist who become emergency patients. The number of scheduled cases that transitioned to unscheduled cases did not impact the renege percentage by more than 1%.

$$\begin{array}{c} Removed\ cases = waitilits\ at\ end\ of\ quarter + new\ cases - \\ completed\ cases - waitlist\ at\ start\ of\ quarter \end{array} \tag{3}$$

$$Renege\ Percentage = \frac{removed\ cases}{waitlist + new\ cases - completed\ cases} \tag{4}$$

The renege rate of each case is illustrated in Table 3.17. Cardiac surgery has the highest renege rate at 35% and plastic surgery has the lowest renege rate at 2%. The majority of the surgical specialties have renege rates below at or below 10% with corresponding non-renege rates greater than 90%.

Table 3.17: Average Renege Rate per Surgical Specialty January 2018 – December 2019 Central Zone

	CARD	GEN	NEURO	OBGYN	OMFD	OPHTH	ORTHO	OTOL	PLAS	THOS	URO	VAS
Renege	36%	10%	4%	9%	6%	8%	5%	9%	2%	7%	7%	7%
Stay	65%	90%	96%	91%	94%	92%	95%	91%	98%	93%	93%	93%

3.5 Current Waitlist Overview

The current waitlist at the end of June 30, 2020 was entered into the model and used as the starting point for analysis. To determine the number of patients on the waitlist at the end of June, the New Cases, Completed Cases, and Waitlist datasets were analyzed using equation 5. The surgery cases on the waitlist were determined by identifying the unique surgery identifying number on each of the Waitlist and New Case data set, which were compared to the Completed Cases data set. The information about the patients on the waitlist included the priority level at the time of the surgical consultation, the procedure code, and the surgical specialty of the patients.

$$Waitlist\ June\ 30, 2020\ (End\ of\ Quarter) = Waitlist\ at\ Start\ of\ Quarter + New\ Cases - Completed\ Cases \quad (5)$$

The current waitlist is comprised of patients of all surgical types and priority levels for scheduled surgeries. Priority levels are numbered one through six with level one being the highest priority and level six being the lowest priority. Unscheduled surgeries are not included in the current waitlist overview as unscheduled patients do not get added to the waitlist. 70% of the current waitlist consists of orthopedic, ophthalmology, and general surgery patients. This is illustrated in Figure 3.5. 95% of the patients on the waitlist have priority levels four to six. The priority level distribution of the patients on the waitlist is presented in Figure 3.6.

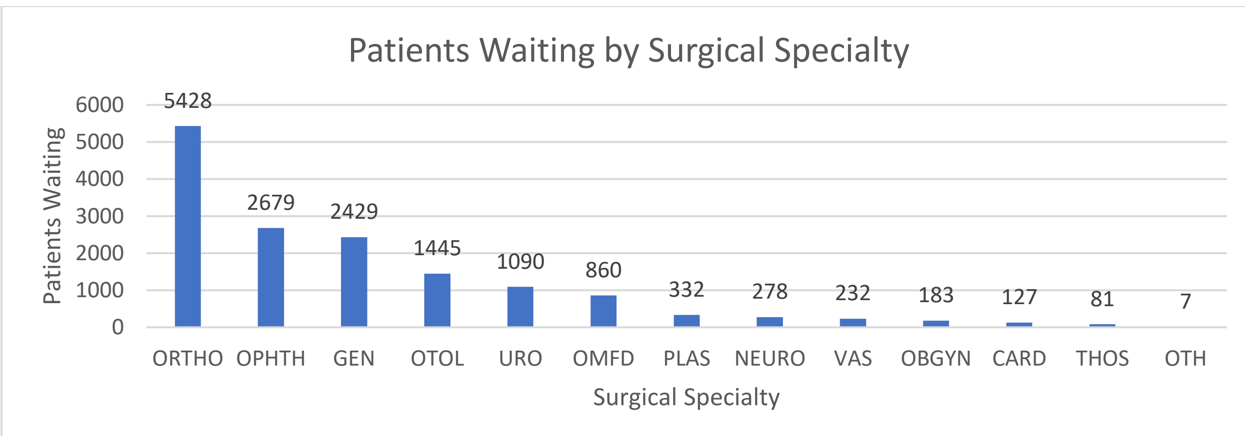

Figure 3.5: Patients Waiting by Surgical Specialty in Central Zone as of June 30, 2020

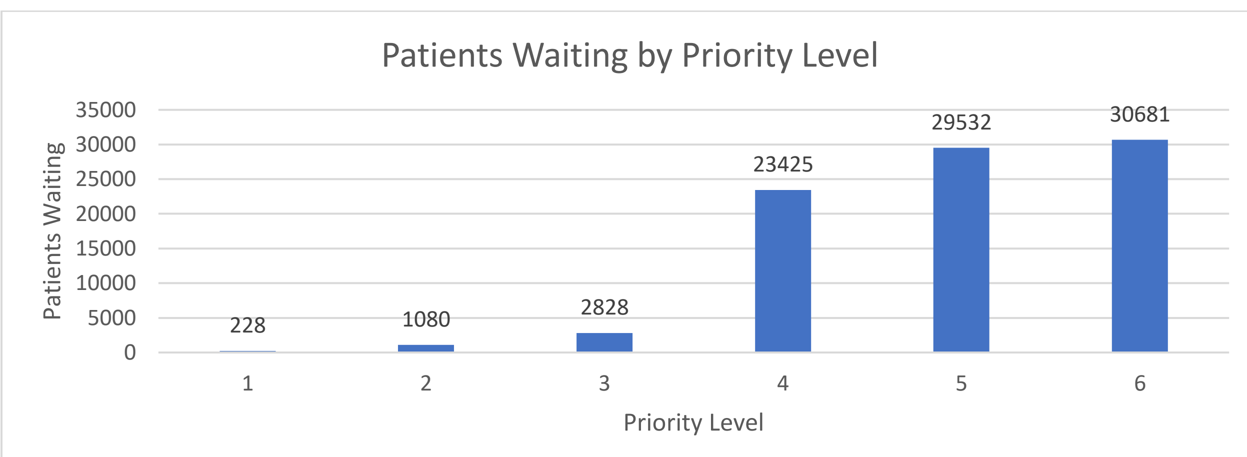

Figure 3.6: Patients Waiting by Priority Level in Central Zone as of June 20, 2020

3.6 New Case Attributes

To further understand the surgical patient mix, and further inform the simulation model, this section explores the types and volumes of patients. Specifically, the new patient arrivals, patient priority level, and inpatient/outpatient classification are stratified by surgical specialty. The high volume procedure codes are also reported.

The proportion of new cases associated with each surgical specialty between January 2018 and December 2019 is presented in Table 3.18. The orthopedic and ophthalmology specialties make up 22.2% and 22.7% of the new cases, respectively. General surgery comprises 17% of the new case attributes. The specialty that contributes the least to the new cases is thoracic surgery at 1.9%.

Table 3.18: New Case Specialty Distribution January 2018 – December 2019 Central Zone

Specialty	Percent
CARD	4.8%
GEN	17.0%
NEURO	3.7%
OBGYN	2.4%
OMFD	2.9%
OPHTH	22.7%
ORTHO	22.2%
OTOL	4.6%
PLAS	2.1%
THOS	1.9%
URO	12.9%
VAS	2.8%

The proportion of cases associated with the seven priority levels for each surgical specialty is displayed in Table 3.19. All of the surgeries for otolaryngology are considered emergency surgeries. Cardiology does not have any new cases of priority level 5 or 6 and is mainly comprised of emergency surgeries and priority 2 cases. General, neurology, orthopedic, plastic, and urology specialties are mostly comprised of emergency surgeries as well as priority levels 4, 5, and 6. Gynecology and thoracic specialty cases enter the system with a majority of priority level 3 cases and ophthalmology surgery has a majority of priority level 4 cases. Oral maxillofacial surgery is the only surgery that enters the system with the majority of cases at a priority level 6. Plastic surgery is mainly emergency surgeries as well as an even distribution of priority levels 3, 4, 5, and 6. Vascular surgery is mainly emergency surgeries, with an even distribution of priority levels 2, 3, 4 and only a few cases of priority 1, 5, and 6.

Table 3.19: Priority Level Distribution per Surgical Specialty

Priority Level	CARD	GEN	NEURO	OBGYN	OPHTH	OMFD	ORTHO	OTOL	PLAS	THOS	URO	VAS
Emergency	33%	41%	37%	7%	5%	9%	27%	100%	32%	27%	33%	46%
1	17%	0%	1%	0%	3%	0%	1%	0%	1%	3%	2%	5%
2	21%	4%	5%	20%	4%	1%	2%	0%	5%	22%	13%	14%
3	12%	8%	8%	38%	6%	1%	6%	0%	17%	36%	14%	12%
4	18%	15%	20%	24%	52%	12%	25%	0%	19%	9%	22%	19%
5	0%	16%	16%	11%	19%	8%	31%	0%	14%	3%	12%	1%
6	0%	15%	13%	0%	11%	70%	8%	0%	13%	2%	5%	3%

Each surgical specialty had a different percentage assigned to each procedure code under that surgical specialty. Due to the large number of specialties and associated procedure codes not all results are presented. The procedure codes for vascular surgeries are presented in Table 3.20. The vascular surgery procedure that is added to the waitlist with the highest frequency is VAS0033 at 17%. The procedure codes with the lowest frequencies are VAS0010, VAS0016, VAS0020 at 0.3%.

Table 3.20: Procedure Code Distribution for Vascular Surgical Specialty

Procedure	Percentage
VAS0001	11.7%
VAS0007	5.6%
VAS0010	0.3%
VAS0012	5.9%
VAS0013	9.0%
VAS0015	7.6%
VAS0016	0.3%
VAS0020	0.3%
VAS0024	11.9%
VAS0027	5.4%
VAS0028	5.7%
VAS0031	13.2%
VAS0033	17.0%

Procedure	Percentage
VAS0035	6.1%

Table 3.21 displays the procedure codes with the highest frequency for each specialty.

Table 3.21: Procedure Codes per Specialty with Largest Percentage

Specialty	Procedure Code	Percentage
CARD	CARD0017	27%
GEN	GEN0032	18%
NEURO	NEURO0119	20%
OBGYN	OBGYN0001	48%
OMFD	OMFD0009	47%
OPHTH	OPHTH0001	65%
ORTHO	ORTHO0053	15%
OTOL	OTOL0038	12%
PLAS	PLAS0006	29%
THOS	THOS0019	65%
URO	URO0021	24%
VAS	VAS0033	17%

The proportion of inpatient and outpatient vascular surgery patients are presented in Table 3.22. The procedure codes illustrate that most procedures are mainly inpatient procedures.

Table 3.22: Patient Status Distribution for Vascular Surgery Procedure Codes

Procedure Code	Inpatient	Outpatient
VAS0001	42%	58%
VAS0007	14%	86%
VAS0010	100%	0%
VAS0012	100%	0%
VAS0013	100%	0%
VAS0015	99%	1%
VAS0016	86%	14%
VAS0020	71%	29%
VAS0024	98%	2%
VAS0027	0%	100%
VAS0028	99%	1%
VAS0031	100%	0%
VAS0033	100%	0%
VAS0035	96%	4%

Table 3.23 displays, the proportion of inpatient and outpatient, for 90% of the surgical specialty. Generally, there are few procedures that contribute to the majority of the cases for each surgical specialty. The table is organized on the specialty percentage. The operating room time per week is displayed to illustrate the distribution of surgical time with respect to how many cases are present on the new case attribute list. The majority of cases are inpatient cases.

Table 3.23: 90% of Surgical Special Distribution of Patient Status by Specialty Percent

Specialty	Specialty Percent	Inpatient	Outpatient	OR Time (hours/week)
OPHTH	23%	2%	98%	63.4
ORTHO	22%	46%	54%	524.7
GEN	17%	71%	29%	357.6
URO	13%	55%	45%	328.2
CARD	5%	73%	27%	178
OTOL	5%	53%	47%	60.2
NEURO	4%	76%	24%	158.2
OMFD	3%	52%	48%	16.4
VAS	3%	85%	15%	173.5
OBGYN	2%	36%	64%	49.6
PLAS	2%	60%	40%	53
THOS	2%	99%	1%	48

4 Model Methods

This section describes the methods used to develop the model. This includes the conceptual and simulation model. The conceptual model details how patients flow through the system and how the patients interact with the system resources described in Subsection 4.1.1. From this the simulation model is programmed and described in detail in Subsection 4.1.2. The parameters and inputs for the simulation follow from the descriptive analytics as described in Subsection 4.1.2.5.

4.1 Model

The model is a discrete event simulation programmed in Python using the SimPy package. SimPy operates with the entities moving through the system as the events which pause for triggered events such as seizing and releasing resources and delaying for a defined. The conceptual model is based on a process flow diagram that was developed in discussions with subject matter experts and based on results from data analysis.

4.1.1 Conceptual Model

The conceptual model was developed in consultation with surgeons as well as support staff NSH. A patient enters the surgical waitlist for elective surgical procedures after a surgical consult is completed. The scope of the conceptual model includes the elective patient process from when the time the surgeon has determined that the patient requires surgery until their length of surgery is complete. Emergency patients are also included from when the decision to have surgery is made until their length of stay is complete. The conceptual model includes emergency patients since they impact the operating room time and hospital beds available for elective surgical procedures.

4.1.1.1 Current System

The process flow for patients on the surgical waitlist is illustrated by the process flow diagram in Figure 4.1.

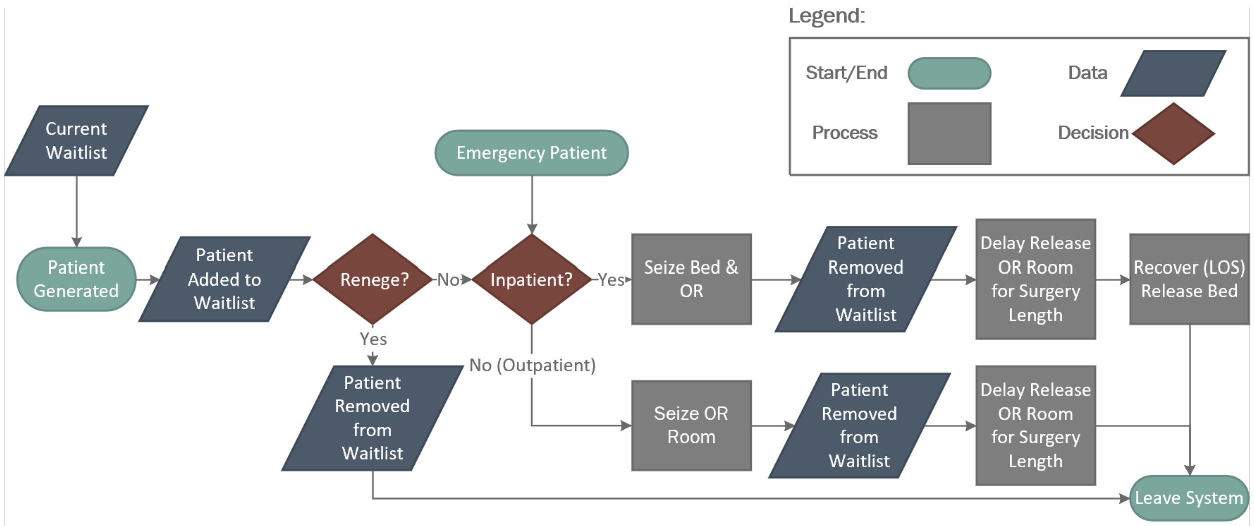

Figure 4.1: Conceptual Model Process Diagram and Legend

Figure 4.1 has two starting points, Patient Generated and Emergency Patient. The elective surgery patients enter through the Patient Generated point at which point the patient is added to the current waitlist which already exists within the system. The waitlist is based on the priority of the patient and when the patient was added to the waitlist. Once a patient enters the patient waitlist the patient either remains on the waitlist until the patient receives surgery or the patient reneges from the system. The patient may renege from the system for a variety for reasons including the patient is no longer eligible for surgery, the patient passed away, or the patient decided they no longer want surgery. The patients that renege from the system are removed from the waitlist and leave the system. Patients renege from the system between when patients are added to the waitlist and prior to being scheduled for surgery.

Emergency patients enter the system but are not added to the waitlist as they are completed as soon as possible. Emergency patients most often present through the emergency department but sometimes are already patients within the hospital. We treat both entry points as one in the model.

All patients are categorized by patient status. Patient status is divided into two categories, inpatient and outpatient. Inpatient procedures require a hospital bed for recovery following the completion of their surgery. An outpatient, on the other hand, leaves the hospital after completing their surgery. Inpatients are removed from the waitlist when they seize the bed in conjunction with an operating room to ensure there is a bed available for the patient to use for recovery following their surgery. The outpatients do not need to obtain a bed and instead move immediately to the operating room when it is available and are removed from the waitlist. Patients retain the operating room for operating room set up, surgical length, and cleaning time. Outpatients simply leave the model after surgery whereas inpatients remain in the hospital to recover from surgery, length of stay. In the true system patients are scheduled in advance and the implications of the relationship between patient status and bed availability is not formally considered by the scheduler. This model aims to evaluate the throughput potential of the system and not the scheduling of patients. The post anesthesia care unit (PACU) is not included as this is considered part of the operating room resources that are required to allow a surgery to occur.

4.1.2 Simulation Overview

The simulation was developed in Python using object-oriented programming. The model runs multiple functions simultaneously to create and communicate the appropriate information to each object type and each object instance. The main components of the model are the Patient Generator, Patient, and Patient Flow classes as well as the Operating Rooms and Hospital Bed resources. The Patient Generator inputs the patients on the current waitlist and generates new patients using the Patient class to assign attributes to the patients. The Patient Flow class contains the functions which describe the journey of the patient through the hospital including the Hospital Stay and Surgery functions. The resources, Hospital Beds and Operating Rooms, are initiated at the beginning of the simulation and are accessible to all classes and functions within the simulation. The data collection throughout the simulation is completed by the Audit function. The data collected includes the waitlist categorized by procedure code, surgery type, and priority level as well as operating room and bed utilization at each hospital. The following subsection details the various functions and classes programmed to reflect the conceptual model. There are 12 classes and 17 functions organized into three categories. The classes, functions, and their associated category are summarized in Table 4.1.

Table 4.1: Code Class and Function Overview

Category	**Class**	**Function**	**Description**
Patient Process	Patient Generator	New Admission	Add patients from current waitlist Generate new patients at a specified interarrival rate
	Patient Class		Assign patient attributes
	Patient Flow	Surgery	Seize, delay, release operating room
		Hospital Stay	Seize, delay, release hospital bed
Resources	Hospital Resource	Check if Bed Available Start	Check queue until a patient is able to seize available resource
		Surgery at Start of Day	
		Can Patient Seize Bed	Check if patient attributes match system criteria
		Place Patient in Bed	Put patient in resource user list
	Operating Room Resource	Operating Room Time Available	Change the operating room time available based on the day of the week
		Set Capacity of Operating Rooms	Check queue until a patient is able to seize available resource
		Check If Operating Room Available	
		Can Patient Start Operation	Check if patient attributes match system criteria
		Put Patient in Operating Room	Put patient in resource user list
Miscellaneous	Audit	Perform Audit	Record model stats every simulated hour
	Arrival Rate	Set Interarrival Rate	Change interarrival rate every month
	Emergency Hours	Set Emergency Schedule	Change emergency hour variable during business hours
	Surgery Initiation	Initiate Surgery at 8:00AM	Start surgeries at 8:00AM everyday
	Operating Room Capacity	Set Operating Rom Capacity	Change operating room capacity when operating room closes/opens
	Hospital	Set Operating Room Daily Hours Available	Change hours available for surgical specialty at each hospital each day

4.1.2.1 Patient Process

The entities within the simulation model are the patients. The basic code for the patient process was developed using the framework by Isken (2017) and Allen (2018) for modelling basic clinical pathways.

4.1.2.1.1 Patient Generator Class

The simulation begins at the Patient Generator Class. First the Patient Generator function imports all the patients currently on the waitlist into the simulation. The simulation remains at time zero until all patients from the waitlist are created. The Patient Generator Class initiates the New Admission function to generate new instances of the Patient Class at intervals determined by the interarrival time. The interarrival rate is exponentially distributed; patients arrive according to a Poisson process. Once the patients are created the Patient Generator sends the patients to the Patient Flow class specific to the surgery group of the patient. Figure 4.2 overviews the simulation initialization code.

```
Algorithm 1a: Patient Waitlist
For Each Simulation
    Generate existing wait list patients according to dataframe; assign the patient attributes
    Generate new patients according to the arrival rate; assign the patient attributes
For Each Generated Patient
    If patient renege attribute is True
        Remove patient from system
    Else
        If patient priority does not equal 1
            Add patient to waitlist
```

Figure 4.2: Algorithm 1a - Patient Waitlist

4.1.2.1.2 Patient Class

The Patient Generator class calls on the Patient class to create a patient instance with specific attributes. The specific attributes of the patient include the patient identification number, operating room, surgical specialty, priority level, renege rate, procedure code, patient status, length of stay, and surgery length. The values for each of these attributes are imported into the system based on historic data and the analyses described in Section 3. The surgical specialty is the first attribute assigned as all other attributes are based on the surgical specialty. All attributes are assigned proportionally based on their frequency in the historical data.

4.1.2.1.3 Patient Flow Class

The patients enter the Patient Flow class from the Patient Generator class. The Patient Flow class models when the patient enters the hospital and then proceeds to surgery. This is modelled using two functions, Surgery and Hospital Stay. The pseudo code for the inpatients and outpatients within the Patient Flow class are in Figure 4.3 and Figure 4.4, respectively.

```
Algorithm 1b: Inpatient Flow
For Each generated Inpatient
    Create Patient Request for a Bed resource based on the patient hospital surgery type attributes
    Seize the first available bed resource
    Update patient hospital attribute
    Remove patient from waitlist
    Send patient to Surgery function
    Create Patient Request for an Operating Room resource based on the patient hospital surgery type
    attributes
    Seize the first available operating room resource
    Delay for the length of surgery
    Release the operating room resource
    Return to Hospital Stay function
    Delay for the length of stay
    Release the bed resource
    Leave the system
```

Figure 4.3: Algorithm 1b - Inpatient Flow

```
Algorithm 1c: Outpatient Flow
For Each generated Outpatient
    Send patient to surgery function
    Create Patient Request for an Operating Room resource based on the patient hospital surgery type
    attributes
    Seize the first available operating room resource
    Remove patient from waitlist
    Delay for the length of surgery
    Release the operating room resource
    Leave the system
```

Figure 4.4: Algorithm 1c - Outpatient Flow

4.1.2.1.3.1 Surgery Function

The Surgery function allows inpatients and outpatients to seize an operating room for the length of the patient's surgery length attribute. Outpatients join the queue for the operating rooms that are available for their specified surgical specialty. Inpatients join the queue for the operating rooms located in the same hospital as their seized bed and specified surgical specialty (seized in the Hospital Stay function). Once the patient has seized an operating room the patient leaves the operating room queue. At this point the outpatients are removed from the waiting list as they were not previously removed. The inpatients wait until the surgery has been completed, release the operating room, and return to the Hospital Stay function.

4.1.2.1.3.2 Hospital Stay Function

The Hospital Stay function within the Patient Flow class encompasses the patients journey through the system that does not include the surgery portion. The reneging patients enter the Hospital Stay function and immediately leave the system prior to surgery. Patients who are not reneging from the system are added to the waitlist.

The inpatients join a queue, or multiple queues, for a hospital bed based on their surgical specialty. The inpatient seizes the bed from the first available resource and leaves the queues of all the other resources. The inpatient is then removed from the waitlist and sent to the Surgery function. Following the inpatient's surgery, the inpatient returns to the Hospital function to complete the length of stay in the hospital bed that was previously seized. The inpatient releases the bed after their length of stay has passed in the simulation and they leave the Hospital Stay function. Outpatients enter the Hospital Stay function and are added to the waitlist. Outpatients then move directly to the Surgery function and return to the Hospital Stay function following the completion of the surgery and immediately leave the Hospital Stay function.

4.1.2.2 Resources

There are two types of resources used in the model, Hospital Bed Resource and Operating Room Resource. The two resources were modified from the priority resource class available in SimPy.

4.1.2.2.1 Patient Request Class

The Priority Request class in SimPy sorts patients in a queue based on the priority of the patient and the time at which the patient enters the queue.(Team SimPy, 2020) A new request class was created called Patient Request which inherits the properties of the Priority Request class but allows an additional input to be used for sorting the Priority Request queue. The additional patient attribute used for sorting is the patient status. The queues are sorted in the following order: patient status, priority level, time the patient entered the queue. Inpatients are given priority as the inpatients have a hospital bed that should not be blocked for longer than the patient requires the bed. The Patient Request class is utilized by both the hospital resource and the operating room resource in the model.

4.1.2.2.2 Hospital Resource Class

The Hospital Resource class is initiated during the simulation set up for each hospital. The Hospital Resource class succeeds events from the queue ensuring patients can only seize resources for which they qualify. Figure 4.5 presents the pseudocode for the two functions Check If Bed Available and Start Surgery at Start of Day. The Check if Bed Available function is activated under two circumstances. The first is when a new Patient Request is added to the queue of the Hospital Bed resource. The second is when a Hospital Bed resource is released by a patient object. The Start Surgery at Start of Day function is called in the Surgery Initiation class. This function is called at the start of every weekday to allow the model to search for elective surgery patients to place in the Hospital Beds to allow surgeries to begin at the start of the day.

```
Algorithm 2: Hospital Resource Class
For Each Hospital Resource Request
    Patient requests a resource creating a Patient Request
    If the number of available resources > 0
        While the index of the current patient is less than the length of the resource queue
            Select the Patient Request at the index location on the queue
            Send the Patient Request to Can Patient Seize Bed function
            If Can Patient Seize Bed function returns True
                Remove Patient Request from queue
                Send Patient Request to Place Patient in Bed function
            If Place Patient in Bed function returns False
                Index =+ 1
            Else
                Number of available resources – 1
                If the number of available resources <= 0
                    Break while loop
```

Figure 4.5: Algorithm 2 - Hospital Resource Class

The Can Patient Seize Bed Function checks the Patient Request that was removed from the queue to determine if the Patient Request matches the system criteria. There are two components of the system state that are evaluated, the emergency hour and the operating hours remaining for the surgery type at the hospital of the Hospital Bed resource.

```
Algorithm 3: Can Patient Seize Bed
For Each Hospital Resource Request
   If Emergency Hour variable == 0
        If patient priority == 1
           Return True
   Else
        If patient surgery length attribute < the number of operating room hours remaining for patient
                                   surgery type at hospital resource
           Decrease the number of operating room hours remaining for patient surgery type at hospital
           resource by the surgery length of the patient
           Return True
        Else
           Return False
```

Figure 4.6 contains the pseudo code for the function Can Patient Seize Bed outlines the process through which the patients' attributes are compared to the system criteria.


```
Algorithm 3: Can Patient Seize Bed
For Each Hospital Resource Request
   If Emergency Hour variable == 0
        If patient priority == 1
           Return True
   Else
        If patient surgery length attribute < the number of operating room hours remaining for patient
                                   surgery type at hospital resource
           Decrease the number of operating room hours remaining for patient surgery type at hospital
           resource by the surgery length of the patient
           Return True
        Else
           Return False
```


Figure 4.6: Algorithm 3 - Can Patient Seize Bed

The function, Place Patient in Bed, is used to finalize the seizing of the resource by the Patient Request. The function places the event into the users list of the Hospital Bed resource.

4.1.2.2.3 Operating Room Resource

The Operating Room Resource is initiated for each operating room within the system. The resource changes capacity, does not allow operating room overtime, and excludes non-emergency patients from receiving surgeries during the evenings and weekends.

Figure 4.7 outlines the removal of Patient Requests from the Hospital Resource queue. Two functions use the code: Check if Operating Room Available and Set Capacity of Operating Rooms. These two functions are used to remove Patient Requests from the Operating Room resource queues until all operating room resources are utilized or there are no Patient Requests in the queue. The Set Capacity of Operating Rooms function is called when the operating room changes capacity. The Check if Operating Room Available function is called when a new Patient Request is added to the queue of the resource or the number of users of the Operating Room resource decreases when it is released by a patient object.

```
Algorithm 4: Operating Room Request
For Each Operating Room Resource Request
    Patient requests a resource creating a Patient Request
    If the number of available resources is greater than zero
        While the index of the current patient is less than the length of the resource queue
            Select the Patient Request at the index location on the queue
            Send the Patient Request to Can Patient Seize Operating Room function
            If Can Patient Seize Operating Room function returns True
                Remove Patient Request from queue
                Send Patient Request to Put Patient in Operating Room function
            If Place Patient in Bed function returns False
                Increase index by 1
            Else
                Decrease the number of available resources by 1
                If the number of available resources is less than 0
                    Break while loop
```

Figure 4.7: Algorithm 4 - Operating Room Request

The Can Patient Start Operation function compares the attributes of the Patient Request to the state of the system, Figure 4.8. There are two components of the system state that are evaluated, the emergency hour and the operating hours remaining for the operating room. During an emergency hour, evenings and weekends, the Patient Request must be an emergency patient for the Patient Request to succeed. The Operating Room Time Available function is used to change time remaining time available for surgeries each day.

Algorithm 5: Can Patient Seize Operating Room

```
For Each Operating Room Request
   If Emergency Hour variable == 0
        If patient priority == 1
            Return True
   Else
        If patient surgery length < total number of hours remaining in the operating room for the day
            Decrease the number of operating room hours remaining for patient surgery type at hospital
            resource by the surgery length of the patient
            Return True
        Else
            Return False
```

Figure 4.8: Algorithm 5 - Can Patient Seize Operating Room

The function, Place Patient in Bed, is used to seize the resource by the Patient Request. The Patient Request is added to the user list of the resource.

4.1.2.3 Miscellaneous

The remaining classes operate concurrently with the previously discussed functions and classes to provide data to the Patient Flow class and the Resource classes. The Audit class is used to record model stats throughout the simulation run. The Perform Audit function, initiated by the Audit class, records the data on an hourly basis. The Arrival Rate class changes the interarrival rate of the patients every month. The Patient Generator class uses the interarrival rate provided by the Arrival Rate class to create a random variate that follows an exponential distribution with a parameter equal to the mean arrival rate. The Emergency Hours class is used to change the emergency hour variable which signals to the system if the current simulation hour is considered an emergency hour or a non-emergency hour. The simulation allows patients of all types to obtain a surgery from 8:00AM to 5:00PM Monday to Friday. The evenings/early mornings as well as the weekends are designated as emergency hours where only emergency patients can seize hospitals beds and operating rooms. The Surgery Initiation Class is used to allow patients to begin seizing Hospital Bed resources at the start of each weekday, 8:00AM. The class is instantiated for each hospital bed resource. The Hospital

Operating Room Time Available class changes variable values associated with each operating room to be equal to the number of hours the operating room is open each day. The Operating Room Capacity class is used to change the capacity of the operating room resources. The class changes the availability of the operating rooms when the operating room changes from opened to closed by changing the capacity from zero, closed, to one, open. Each operating room has a different number of hours that it is open during the day with most not being open more than ten hours a day.

4.1.2.4 Model Assumptions

Assumptions were made during the development of the conceptual model to ensure the level of detail matched the desired analysis. The assumptions encompass the complexity of the movement of patients in the system as well as the variability present in the system.

The priority level of the patients does not change over time in the model. The patients enter the system with a priority level designated to them by the surgeon at their initial consultation. The priority level does not change while the patient is on the waitlist. This is a simplification of the system as the priority level of the patient can change over time. However, there is not a uniform process for which priority levels change over time. Some of the factors that affect the priority level of the patients include the length of time the patient has been waiting as well as new or worsening symptoms. The model would need to include a variation of accumulating priority queues. (Stanford, Taylor, & Ziedins, 2014) This increased complexity was deemed not necessary for the desired analysis and output. The goal of the model is to evaluate the overall throughput of the system and to measure the impact on the waitlist. The addition of an accumulating priority queue was not necessary for studying the overall throughput of patients.

The goal of the model did not include optimizing the elective surgery schedule instead this historical realized schedule is used. In the current system patients are scheduled approximately two to four weeks in advance. The model does not schedule surgeries in advance, the model evaluates the available time remaining in the operating room for that day and allocates surgeries that can be completed before the end of day. The model searches the entire queue to determine if any patient in the queue can fill in the unused operating room time to facilitate an evaluation of the potential patient throughput in the system. This is perhaps more efficient than the actual system which works with a two to four week delay between scheduling and surgery. This delay could cause surgeries to be cancelled which would not occur in our model. Discussions with subject matter experts and observations of the system illustrated surgery cancellations are avoided at all costs. Our model also always assumes the patient is available for surgery. In practice this might not be true but the next available patients will simply be scheduled as a result.

In the real world, operating rooms are scheduled leaving approximately an hour of unscheduled operating room time. This time is allocated as a buffer to allow for unexpected delays in the operating room or prior to entering the operating room. Hospital policy allows operations to proceed if the expected overtime does not exceed approximately 30 minutes. The base model does not incorporate the buffer or exceedance allowance but instead searches the queue to find highest priority patient that fits in the remaining operating room time. As shown in the validation section, this simplification results in the same patient throughput as observed in the historical data.

The resources modelled in the system are the operating rooms and the inpatient beds. This is a simplification of the real system as there are many other resources such as nurses, equipment, and surgeons that are also considered during the scheduling of a procedure. This assumption implies that there is sufficient staff and equipment available for all opened beds. This is consistent with typical operations.

The arrival rate of patients to the system was based on when patients are added into the electronic database. The addition of patients to the database is dependent on the administrative staff. The method used to input patients to the system varies and can be completed in batches or immediately when the consultation is completed. The model smooths the arrival of the patients over time to allow patients to enter the waitlist at regular intervals. The intervals change based on the month of the system but not based on the hour or day of the week. This removes the variability of patients being entered in bulk or the variability of patients only arriving during business hours. This better reflects the actual time the patient began waiting instead of the time they were entered into the database.

The surgical procedure times in the system encompass the entire time the operating room is occupied by the scheduled surgery. This includes the time from when the operating room is ready to when the operating room has finished being cleaned after a procedure. It is important to consider all aspects not just the times at which the surgeons or the patients are in the room as the operating room can not be used by another patient during the preparation and cleaning times.

4.1.2.5 Model Parameters

The parameters of model reflect the real world by generating random variate from distributions fit to historical data as discussed in Chapter 3, Descriptive Analytics. The simulation was run for a year and six months, 15,171 hours, and ten replications. The number of replications was determined based on Equation 6. A simulation run of ten replications was used to determine the standard deviation, s, of the waitlist length at the end of the simulation run time. The accepted half width, E, was 175 patients, and the confidence level, α, was 0.05. Ten replications resulted in the desired level of confidence in the model output. The audited data was averaged for each hour of the ten replications to ensure the stochastic nature of the model was captured in the model output. The warm up period was based on the length at which it takes the simulation to utilize the all hospital bed resources. An analysis of the model output determined this time was 7 weeks. The run time of the simulation was a year and a half.

$$n \geq \left(\frac{t_{n-1, \alpha/2} S}{E} \right)^2 \tag{6}$$

5 Model Validation and Verification

The model development incorporated numerous validation and verification methods outlined by Law (2013) in Simulation Modelling and Analysis. This included slow build, trace, simplified characteristics, and data tracking. The verification and validation techniques listed were used simultaneously throughout the model development to facilitate a thorough and detailed analysis of the model at each stage of the development.

5.1.1 Slow Build

Law (2013) described developing a simulation model using a slow building technique which is defined as "…write and debug the computer program in modules or subprograms."(Law, 2013) The simulation model was developed slowly to allow for the detail to be gradually added while ensuring issues were identified immediately. For example, the hospital stay component was initially added to the model with only one bed resource and one operating room to simplify the development of the hospital stay components. Detail was added to the hospital stay function by incorporating more resources and designating which resources were available to which surgery specialties after the simplified program was verified. This slow build approach helped debug a logic error that appeared when additional bed and operating room resources were added.

5.1.2 Trace

The trace technique as described by Law as "…the state of the simulated system… are displayed just after each event occurs and are compared with hand calculations to see if the program is operating as intended." (2013) The trace method facilitated the identification of many bugs within the code. For example, the model outputted a variety of time stamps from which it was identified that some patients were leaving the hospital prior to the end of the length of stay. This was caused by the length of stay delay happening in parallel with the surgery delay instead of subsequent to the surgery delay. The trace facilitated the correction of the bug allowing the patients to wait until the surgery was completed before moving through the remaining portion of the system. This process was carried through as the code became more complex to ensure the correct patients were accessing the correct hospitals and operating rooms and releasing the resources at the appropriate times.

5.1.3 Simplified Characteristics

The third method that was utilized throughout the development of the model that was used in conjunction with the two methods described in Subsections 5.1.1 and 5.1.2 was running the model with simplified characteristics. "The model should run, when possible, under simplifying assumptions for which its true characteristics are known or can easily be computed." (Law, 2013) Simplifying the characteristics facilitates better use of the other verification and validation methods as it allows for hand calculations to be computed easily. The simplified characteristics was mainly used in controlling the attributes of the patients and the number of resources available. Controlling the attributes of the patients included giving all patients the same length of stay, only allowing outpatients or inpatients, removing all surgical specialties except one or two surgical specialties, as well as giving all patients the same priority level. Simplifying these attributes of the patients controlled what aspects of the model were used by the patients and facilitated targeted analysis of the model functions.

5.2 Model Data

To further verify and validate the model. The utilization of the resources, operating rooms and beds within the simulation model was computed.

5.2.1 Data Input Values

The distribution data used in the model was analyzed using a Kolmogorov-Smirnov (K-S) test to determine if the empirical distribution data produced from the model was statistically different than the historical sample data. The K-S test was selected as it compares the data produced from the model with real life data to determine if the data came from the same distribution. The K-S test was performed on all surgery length and length of stay distributions that were developed. The null hypothesis could not be rejected for 65% of the length of stay distributions developed at a 5% significance level. The null hypothesis, the model output data matched the data from NSH, could not be rejected for 37% of the surgery length distributions developed at a

5% significance level. Table 5.1 displays the percent of the K-S tests for the procedure code for each surgical specialty which produced a p-value which could not reject the null hypothesis.

Table 5.1: Surgery Length and Length of Stay Distribution Comparison

	Surgery Length		Length of Stay	
Surgical Specialty	Count	P-Value	Count	P-Value
CARD	11	55%	8	63%
GEN	76	62%	51	37%
NEURO	33	76%	22	59%
OBGYN	14	71%	6	17%
OMFD	7	57%	4	25%
OPHTH	14	86%	7	14%
ORTHO	51	63%	29	28%
OTOL	24	42%	16	13%
PLAS	17	88%	8	38%
THOS	14	79%	10	50%
URO	42	67%	23	35%
VAS	12	50%	9	56%
Total	315	65%	193	37%

Table 5.2 illustrates the distribution of cases for each specialty in the model data and the real data that was provided by NSH. A chi-square test can be used for discrete distributions to determine if the observed number of observations is different from the expected number of observations. A chi-square test produced a p-value of 0.904 which fails to reject the null hypothesis that the two distributions are equal. Thus, the proportion of surgical specialties produced by the model is not statistically different from the inputted discrete distribution.

Table 5.2: New Case Specialty Verification

Specialty	Model Data Count	Real Data Proportion
CARD	3,733	4.8%
GEN	13,190	17.0%
NEURO	2,911	3.7%
OBGYN	1,818	2.4%
OMFD	2,173	2.9%
OPHTH	17,600	22.7%
ORTHO	17,341	22.2%
OTOL	186	4.6%

Specialty	Model Data Count	Real Data Proportion
PLAS	3,607	2.1%
THOS	1,592	1.9%
URO	1,424	12.9%
VAS	9,910	2.8%

The number of patients which acquired each priority level for each surgical specialty was compared to the proportion of cases with each priority level from the data using a chi-squared test. All surgical specialties failed to reject the null hypothesis except for thoracic surgery which had a p-value of 0.033, as shown in Table 5.3.

Table 5.3: Priority Level Discrete Distribution Verification Per Surgical Specialty

Specialty	Data Type	Priority							P-Value
		1	2	3	4	5	6	7	
CARD	Data Proportion	33%	17%	21%	12%	18%	0%	0%	0.500
	Model Data	1,211	664	745	422	690	1	0	
GEN	Data Proportion	41%	0%	4%	8%	15%	16%	15%	0.376
	Model Data	5,362	34	483	1,129	2,039	2,149	1,994	
NEURO	Data Proportion	37%	1%	5%	8%	20%	16%	13%	0.544
	Model Data	1,051	39	153	227	594	441	406	
OBGYN	Data Proportion	7%	0%	20%	38%	24%	11%	0%	0.710
	Model Data	125	6	384	664	435	204	0	
OPHTH	Data Proportion	5%	3%	4%	6%	52%	19%	11%	0.844
	Model Data	914	484	758	1,056	9,085	3,328	1,975	
OMFD	Data Proportion	9%	0%	1%	1%	12%	8%	70%	0.926
	Model Data	206	7	12	19	255	167	1507	
ORTHO	Data Proportion	27%	0%	2%	5%	25%	31%	8%	0.135
	Model Data	4,694	106	400	924	4,419	5,372	1,426	
OTOL	Data Proportion	100%	0%	0%	0%	0%	0%	0%	N/A
	Model Data	3,607	0	0	0	0	0	0	
PLAS	Data Proportion	31%	1%	5%	17%	19%	13%	13%	0.930
	Model Data	483	18	89	270	305	227	200	
THOS	Data Proportion	27%	3%	22%	36%	8%	3%	1%	0.714
	Model Data	381	37	320	516	103	45	22	
URO	Data Proportion	33%	2%	13%	14%	22%	12%	5%	0.827
	Model Data	3,253	222	1,261	1,314	2,190	1,128	542	
VAS	Data Proportion	46%	5%	14%	12%	19%	1%	3%	0.033
	Model Data	959	122	312	286	379	8	78	

The proportion of cases in the data set which reneged from the system was compared to the number of patients that reneged from the model for each surgical specialty using a chi-squared test. Table 5.4 displays the p-values and all surgical specialties failed to reject the null hypothesis.

Table 5.4: Renege Rate Model Data Verification

	Renege		Stay		
Specialty	Model Data	Data Proportion	Model Data	Data Proportion	P-Value
CARD	1,384	36%	2,349	65%	0.171
GEN	1,276	10%	11,914	90%	0.212
NEURO	116	4%	2,795	96%	0.967
OBGYN	158	9%	1,660	91%	0.645
OMFD	132	6%	2,041	94%	0.884
OPHTH	1,447	8%	16,153	92%	0.279
ORTHO	813	5%	16,528	95%	0.481
OTOL	319	9%	3,288	91%	0.743
PLAS	45	2%	1,547	98%	0.132
THOS	94	7%	1,330	93%	0.555
URO	737	7%	9,173	93%	0.674
VAS	166	7%	1,978	93%	0.471

The proportion of cases in the data set which were assigned to each procedure code in each surgical specialty was compared to model procedure code data for each surgical specialty using a chi-squared test. All but two, vascular and thoracic surgery, surgical specialties rejected the null hypothesis as displayed in Table 5.5.

Table 5.5: Procedure Code Distribution Verification

Specialty	CARD	GEN	NEURO	OBGYN	OMFD	OPHTH	ORTHO	OTOL	PLAS	THOS	URO	VAS
P-Value	0.894	0.912	0.056	0.431	0.036	0.793	0.627	0.538	0.367	0.01	0.685	0.037

The arrival rate of the new patients to the system was accurately represented in the model. The interarrival rate followed an exponential arrival rate for most months except for February. The arrival rate represented the arrival rate seen in the data. The data is summarized in Table 5.6.

Table 5.6: Arrival Rate Model Input vs. Model Output

	Arrival Rate		Exponential Distribution
Month	Input	Output	P-Value
January	4.98	5.09	0.132
February	4.73	4.76	0.016
March	4.00	3.92	0.528
April	4.40	4.50	0.659
May	4.60	4.67	0.095
June	4.36	4.37	0.524
July	4.12	4.14	0.855
August	3.95	3.99	0.116
September	4.74	4.71	0.830
October	4.59	4.61	0.589
November	4.77	4.78	0.560
December	3.84	3.98	0.595

5.3 Sensitivity Analysis

The sensitivity analysis aims to understand the impact of chosen model parameters on the model output. The sensitivity analysis is completed using a 2k factorial experiment design. The analysis of the effects of the experiments aims to identify the impact of the interactions of the model parameters and the impact of the individual parameters on the chosen metric. The chosen metric is the length of the waitlist at the end of simulation. There were four factors that were changed resulting in 16 experiments. The parameters chosen for the experiment designs were arrival rate, patient status distribution, length of stay, and bed capacity. Each of the parameters were assigned a high and a low parameter. The arrival rate was reduced by two per hour for the low parameter and increased by two per hour for the high parameter from the original arrival rates. The low parameter experiment for the patient status changed all procedures that could be both outpatient and inpatient procedures to only inpatient procedures, resulting in a low number of outpatient procedures. The high parameter experiment for the patient status did the reverse of the low experiment, all procedures that could be both outpatient and inpatient procedures were only outpatient procedures. The length of stay of the patients were decreased to 25% of the original length of stay for the low experiment and doubled for the high experiment. The number of beds available was reduced to

50% for the low value and doubled for the high value. Table 5.7 outlines the experiment model runs, high and low are represented by “+” and “-“, respectively.

Table 5.7: 2^k Factorial Experiment Design

Experiment	Arrival Rate	Patient Status	Length of Stay	Bed Capacity
1	+	-	-	-
2	+	+	-	-
3	+	+	+	-
4	+	-	+	-
5	-	-	-	-
6	-	+	-	-
7	-	-	+	-
8	-	+	+	-
9	+	-	-	+
10	+	+	-	+
11	+	+	+	+
12	+	-	+	+
13	-	-	-	+
14	-	+	-	+
15	-	-	+	+
16	-	+	+	+

The sensitivity analysis was performed using Minitab. The R^2 value of the model is 99.83% which indicates the model fits the data well. The analysis of variance produced is displayed in Table 5.8. The analysis indicates the arrival rate, patient status, and bed capacity have effects that are statistically significant. However, the length of stay does not have a statistically significant impact. The two way interactions demonstrate that the arrival rate and the patient status as well as the patient status and bed capacity should not be considered without considering the interaction effect. The Pareto chart in Figure 5.1 indicates patient status has the largest effect on the patient waitlist whereas bed capacity has the smallest effect whilst still having an effect.

Table 5.8: Sensitivity Analysis Factorial Design

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	10	14895112202	1489511220	289.99	0.000
Linear	4	13984233559	3496058390	680.63	0.000
Arrival Rate	1	5914582825	5914582825	1151.48	0.000
Patient Status	1	8007847105	8007847105	1559.01	0.000
Length of Stay	1	9951028	9951028	1.94	0.223
Bed Capacity	1	51852601	51852601	10.09	0.025
2-Way Interactions	6	910878643	151813107	29.56	0.001
Arrival Rate*Patient Status	1	824156441	824156441	160.45	0.000
Arrival Rate*Length of Stay	1	1565564	1565564	0.30	0.605
Arrival Rate*Bed Capacity	1	18549172	18549172	3.61	0.116
Patient Status*Length of Stay	1	10943691	10943691	2.13	0.204
Patient Status*Bed Capacity	1	55420208	55420208	10.79	0.022
Length of Stay*Bed Capacity	1	243567	243567	0.05	0.836
Error	5	25682549	5136510		
Total	15	14920794751			

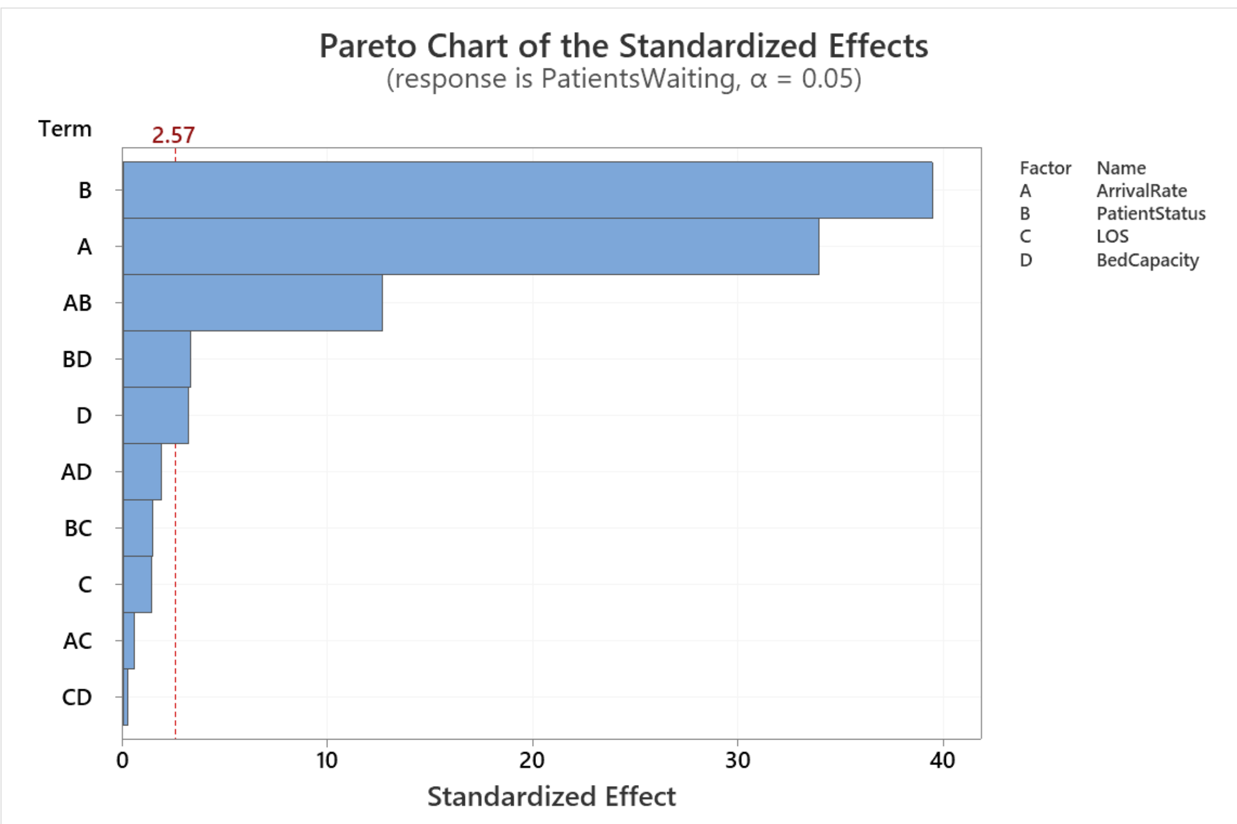

Figure 5.1: Pareto Chart of the Standardize Effects of the Factorial Design

5.4 Summary

The verification and validation performed on the model began in the development of the model. The techniques that are were used, slow build, trace, and simplified characteristics, allowed the development of the model to be robust. The model facilitated the analysis of the model output as compared to the desired results. The new case distribution for surgical specialty and renege rate matched the expected output. The procedure code matched the expected output for all surgical specialties except thoracic and vascular surgery. Priority level distributions matched the expected output for all but thoracic surgery. The length of stay distributions that were developed only matched 65% of the procedure codes. This is acceptable because the sensitivity analysis indicated the length of stay does not have an impact on the model results. The sensitivity analysis also indicated the arrival rate and patient status have a large impact on the model. The arrival rate of the patients matched the system input and was sensitive to the specific month. The patient status was identified for each procedure code, not for the overall surgical specialty, which achieved the highest level of sensitivity possible with the data provided. Thus, the method of development facilitated a robust and sensitive model which simulated the environment as expected.

6 Experiments

The experiments performed using the discrete event simulation model were categorized into three categories. Each of the experiments were developed using the model described in Section 4 as the base model. The base model was used to develop the experiments by applying the changes described below.

The first category is COVID-19 Recovery scenarios where the system is operating at 100% of the pre-COVID-19 capacity. This represents the hospital system in between large waves of COVID-19 as well as after the pandemic has concluded. The waitlist that accumulated during the shutdowns caused by waves of COVID-19 are the focus of the COVID-19 recovery experiments. The resource allocation levels and forced changes in demand are the general categories of scenarios that were explored.

The second category involves modelling waves of COVID-19, titled COVID-19 Effects. The first wave affected the hospital systems drastically as the implications and effects of COVID-19 were not known. Thus, understanding the implications of subsequent waves on the healthcare system can facilitate the appropriate preparation necessary.

The final category is a section which combines previously discussed experiments to understand the impacts. The most effective COVID-19 Recovery efforts are combined to determine at which point a steady state or a continuously decreasing waitlist exists. Further, the COVID-19 Recovery scenarios are combined with the COVID-19 Effects to determine the effects of varying resource allocation levels in different post COVID-19 environments.

A summary of the designed experiments is provided in Table 6.1.

Table 6.1: Experiment Summary

Category	Experiment	Description
COVID-19 Recovery	Two Hours of Overtime	Each operating room is available an extra two hours each day of the week
	Scheduled Surgeries on Weekends	Scheduling surgeries on weekends during the day time
	Hospital Bed Capacity	Increasing the hospital bed capacity by 10% and 25%
	Increased Number of Outpatients	Increase the percentage of operations that already allow outpatients by 10%
	Decreased Length of Stay	Decrease the length of stay of all patients by 25%
COVID-19 Effects	Increased Cleaning Time	Double the cleaning time for all procedures and add one hour of cleaning time for vascular, cardiology, and thoracic surgery.
	Increased Demand	Increasing the demand that was not seen in the system during the first wave in the following months
	Increased Cleaning Time & Demand	Combine Increased Cleaning Time and Increased Demand scenarios.
Combination	COVID-19 Recovery	Combine the most effective COVID-19 Recovery scenarios
	COVID-19 Effects and Recovery	Combine Increased Cleaning Time and Demand experiment with the COVID-19 Recovery scenarios

6.1 COVID-19 Recovery

The end of the first wave of the pandemic in Nova Scotia in August of 2020, allowed elective surgical procedures to operate at 97% capacity (Grant, 2020). The following experiments were designed to understand how altering the resource and demand impacts the waitlist as compared to the base system.

6.1.1 Resource

The resource experiments pertain to altering the operating room hours and the number of beds available at the hospitals. Three experiments were performed: adding operating room overtime, weekend elective procedures, and increasing the bed capacity.

6.1.1.1 Two Hours of Overtime

The experiment allowed the operating rooms to operate with two hours of overtime each day. Operating room overtime is not allowed within the base model. Ontario Health (2020) and British Columbia Ministry of Health (2020) listed extending operating room hours as one of the strategies to address the surgical backlog. In the base model, when a patient object requests an operating room resource the model checks to ensure there is enough time remaining in the day for the patient to complete their surgery. If there is no patient on the waitlist that can complete the surgery within the remaining time available, the operating room goes unused. To allow the operating rooms to be used more, this experiment permits operations to proceed if the operations can finish within two hours after the operating room closes for the day. In this scenario the model checks to see if the surgery length of the patient is less than the time remaining plus two hours. When a patient object matches this criteria the patient seizes the operating room.

6.1.1.2 Scheduled Surgeries on Weekends

The experiment allowed the operating rooms to operate on the weekends. The idea of working weekends was suggested by British Columbia Ministry of Health (2020) as this is currently a standard strategy for waitlist management. The experiment alters the base model as the base model allows only unscheduled surgeries to occur in designated emergency operating rooms on the weekends. The operating rooms designated for emergency use are available all hours on the weekend with scheduled surgeries allowed between 8AM and 5PM. The experiment also opens all operating rooms on Saturday and Sunday according to their Friday schedule.

6.1.1.3 Hospital Bed Resource Levels

The experiment focused on the bed resources at the hospitals. It is often discussed that bed capacity is the most limiting factor on admitting patients to hospitals (Office of the Auditor General, 2016) as well as the number of surgeries that can be performed. Further, increasing the hospital capacity is often considered a post COVID-19 surgery resource allocation strategy. It is identified by BC Health that hospitals needed to create 15% more capacity to allow the hospitals to perform more surgeries (British Columbia Ministry of Health, 2020). At each site, the experiment increased the beds available to the surgery department by 10% and 25%. The range was chosen because an increase more than a 10% is likely not feasible given physical restrictions of hospitals. That said, an increase of 25% will help more thoroughly explain the impact of the bed constraints.

6.1.2 Demand

There were two demand related experiments performed on the model. Altering the demand to the system is difficult to implement in practice as the demand is stimulated by the population and not the system. The surgical demand and the number of surgeries required can not be altered but how that demand is fulfilled can be. For example, the overall demand can be impacted by completing some inpatient procedures as outpatient procedures and by reducing the length of stay of the inpatient procedures.

6.1.2.1 Increased Number of Outpatients

The experiment increased the proportion of patients completed as outpatients. The procedure codes that had both inpatients and outpatients were altered to decrease the number of inpatients by 10% and increase the number of outpatients by 10%. The alteration of procedure codes which currently are only inpatient procedures would require the input from subject matter experts to determine the feasibility of the change and were therefore not altered.

6.1.2.2 Decreased Length of Stay

The experiment was decreasing the length of stay of patients in the system. It is difficult to reduce the length of stay of patients within the hospital system. However, allocating the patients to other areas of the hospitals to allow other surgical patients to recover in the surgical beds is a possibility. This is a possibility as outlined by the British Columbia Ministry of Health required hospitals to create an added 15% bed capacity (British Columbia Ministry of Health, 2020). Further, it was important to understand interaction between the length of stay of the patients and the overall bed usage to understand the impact length of stay has on the overall throughput of inpatients. The overall length of stay of the patients was reduced by 25% to be 75% of the original length of stay.

6.2 COVID-19 Effects

Elective surgical procedures were cancelled due to the implications of COVID-19 on the hospital system as well as the risk to the patients during the first wave of COVID-19 in Nova Scotia (Cooke, 2020). The experiments performed on the resource allocation levels incorporated increased surgical cleaning and preparation time due to COVID-19 safety procedures. The demand was also altered to understand the impact to the system of an increase in surgical demand due to the healthcare systems initial lock down as well as the result of very little demand during a second wave.

6.2.1 Increased Cleaning Time

An additional experiment that was evaluated was increasing the operating room sanitation time due to COVID-19 protocols. Guidelines surrounding the cleaning procedures for operating rooms during COVID-19 have resulted in increased cleaning time following a surgical procedure. The impact of the cleaning on the overall patient throughput of the system was important to identify. The cleaning time for all surgical procedures was doubled to account for the new protocols. Secondly, the cleaning time for surgeries for thoracic, cardiology, and otolaryngology was increased by one hour as these surgeries have been identified as requiring increased COVID-19 procedures due to the surgical characteristics.

6.2.2 Increased Demand

The experiment incorporates the demand that was lost during the initial wave of the pandemic the arrival rate decreased in the months following the end of the first wave. This was due to patients not consulting with surgeons which resulted in patients not being added to the waitlist during the first wave. However, the need for surgery did not actually get “lost” during the pandemic and these patients who did not receive consults during this time should eventually enter the system. This was articulated by Dr. Gregory Hirsch, senior medical director of surgical services at NSH, "We're anticipating … a flood of patients coming through, but they haven't quite arrived yet."(Grant, 2020) In the experiment, the unseen demand was added to the normal demand seen, during June 2020-December 2020. The arrival rate of the patients increased during those six months to account for the lost demand of the system.

6.3 Combination of Experiments

A combination of the experiments presented in the previous subsections of this section, 6.1 and 6.2, are described.

6.3.1 Effective COVID-19 Recovery Experiments

The results of the COVID-19 Recovery experiments provide insight into a combination of recovery scenarios that would most effect the COVID-19 waitlist. The most effective COVID-19 Recovery scenarios are combined with the goal of obtaining a steady state or continuously decreasing patient waitlist.

6.3.2 COVID-19 Effects with COVID-19 Recovery Methods

The COVID-19 Recovery experiments were applied to the COVID-19 Wave experiments to understand the interactions between the recovery approaches and the potential further effects of COVID-19. Further, the COVID-19 Wave experiments were combined to model the effects of COVID-19 that were already present in the system. The COVID-19 Wave experiments that were combined were the increased demand and the increased cleaning time. The increased cleaning time is currently being seen in the system and the increased demand is expected to enter the system. This experiment was added to the list of COVID-19 Wave experiments that were analyzed using the COVID-19 Recovery methods.

7 Results

The results from this study appear in this chapter. Section 7.1, overviews the existing data and the simulation model output for the base model. The base model is the scenario where no interventions are used and the system parameters match those prior to the arrival of COVID-19 in Nova Scotia. Section 7.2 presents results for each of the experiment discussed in Chapter 6.

7.1 Base Model

The base model of the system provided results on the waitlist length. The following figures illustrate the waitlist length for different patient attributes over a year and a half period. The waitlist length for each surgical specialty over time, as well as the total patient waitlist, is displayed in Figure 7.1. The July 1st data (displayed on the origin Figure 7.1) is the actual waitlist computer from the historical data. The remaining data presented in Figure 7.1 is produced by the discrete event simulation model.

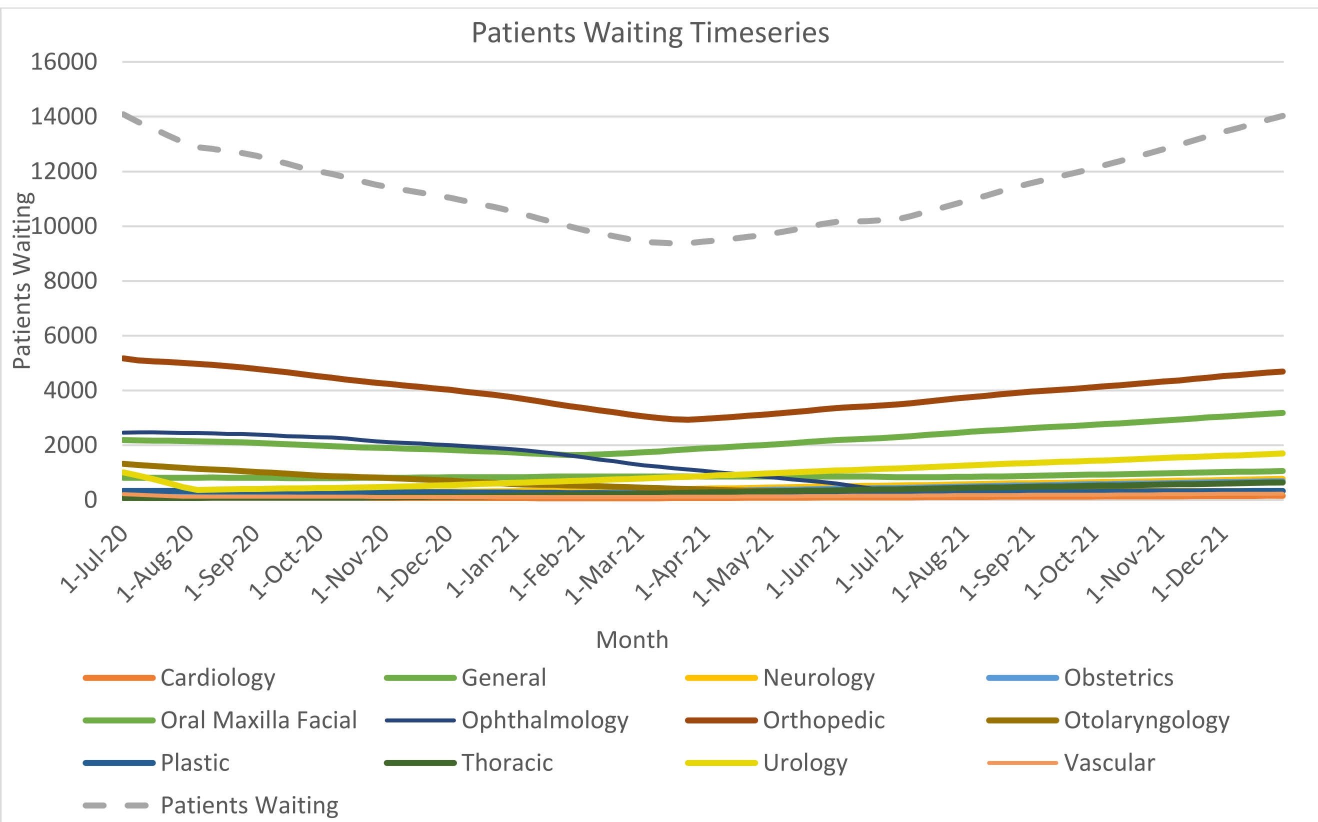

Figure 7.1: Base Model Patient Waiting Timeseries

As seen in Figure 7.1, the total patients waiting waitlist was comprised mainly of orthopedic, general, and urology surgery. The orthopedic surgery displays identical shape characteristics to the total patients waiting waitlist. Further, from Figure 7.1, we see that for the first eight months following July 1 the overall waitlist length, and most specialties, see a decline in their waitlist length. The following months display a steady increase in the waitlist length. To explore the feature, the waitlist length segregated by inpatient and outpatient is plotted as displayed in Figure 7.2.

The waitlist length of the patient status, inpatient and outpatient, is displayed in Figure 7.2 along with the total number of patients waiting.

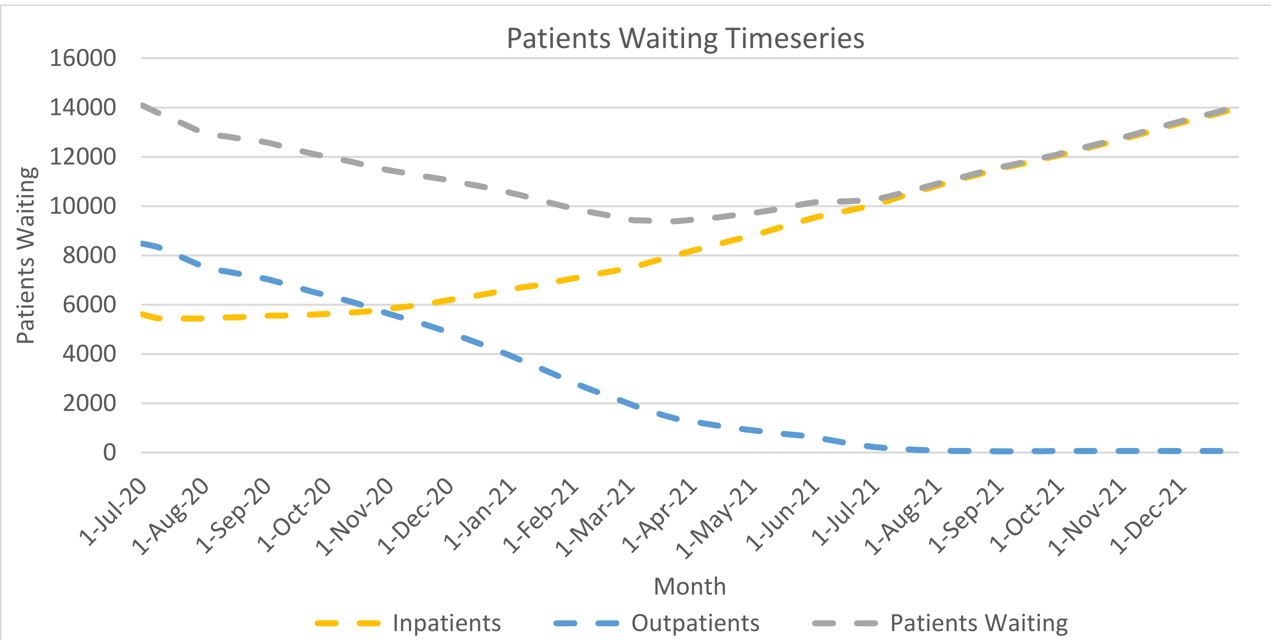

Figure 7.2: Inpatients vs. Outpatients Patients Waiting Timeseries

From Figure 7.2 we see decline in waitlist length can be attributed to outpatients leaving the waiting list within one year the majority of outpatient can have surgery. Despite this the overall waitlist grows (after eight months) due to inpatients.

The utilization of the operating room per week was calculated for the duration of the simulation model and is presented alongside the number of patients waiting in Figure 7.3 for general surgery. The primary y-axis (left) is the operating room utilization per week and the secondary y-axis (right) is the number of patients waiting per week. The remaining surgical specialties are presented in Appendix B. The utilization of the operating rooms significantly decrease when the number of outpatients reaches a steady state.

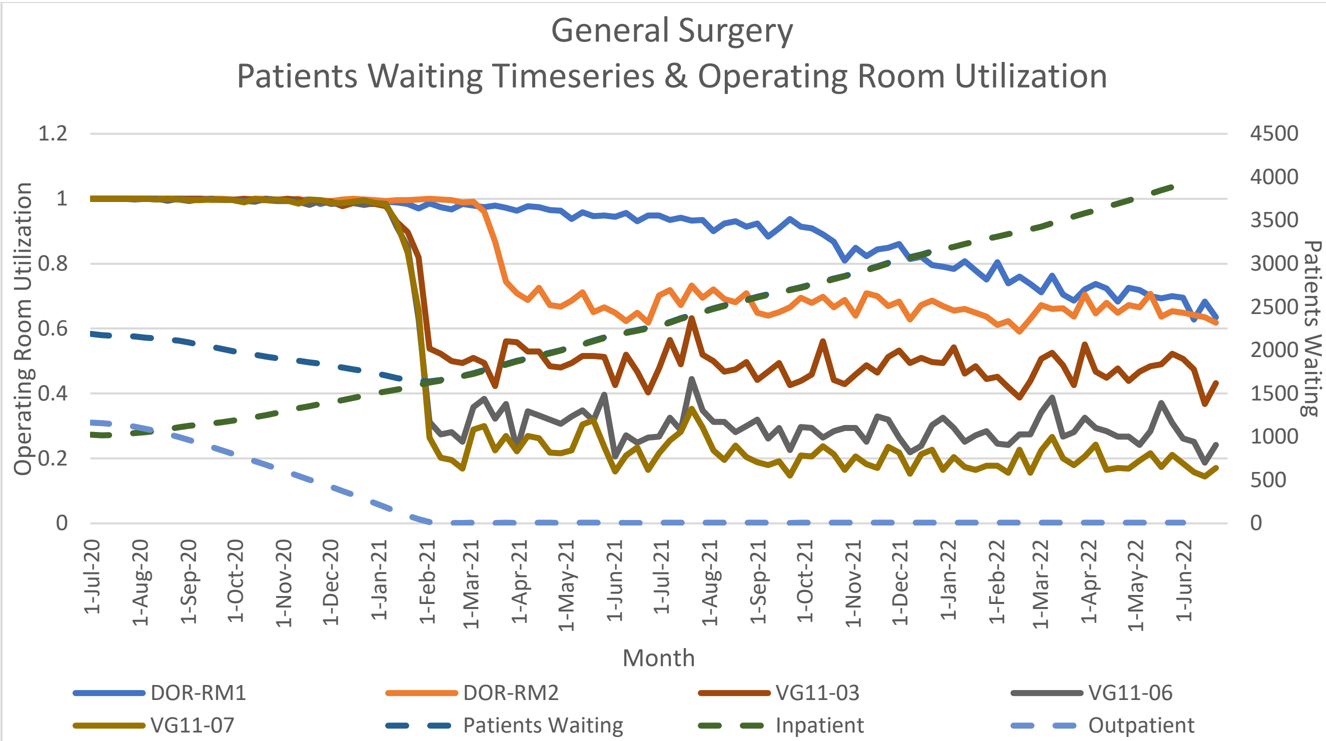

Figure 7.3: General Surgery Patients Waiting Timeseries & Operating Room Utilization

7.2 Experiments

The results of the experiments discussed in Chapter 6 are presented below. The model initiates at the state of the actual state of the system on July 1, 2020. The data presented following that date is derived from the model.

7.2.1 COVID-19 Recovery

The results from the COVID-19 Recovery experiments are displayed in Figure 7.4. All of the experiments performed favorably to the base model. Allowing two hours of overtime in the system has the greatest overall impact on the waiting list whereas decreasing the length of stay to 75% produced the smallest impact.

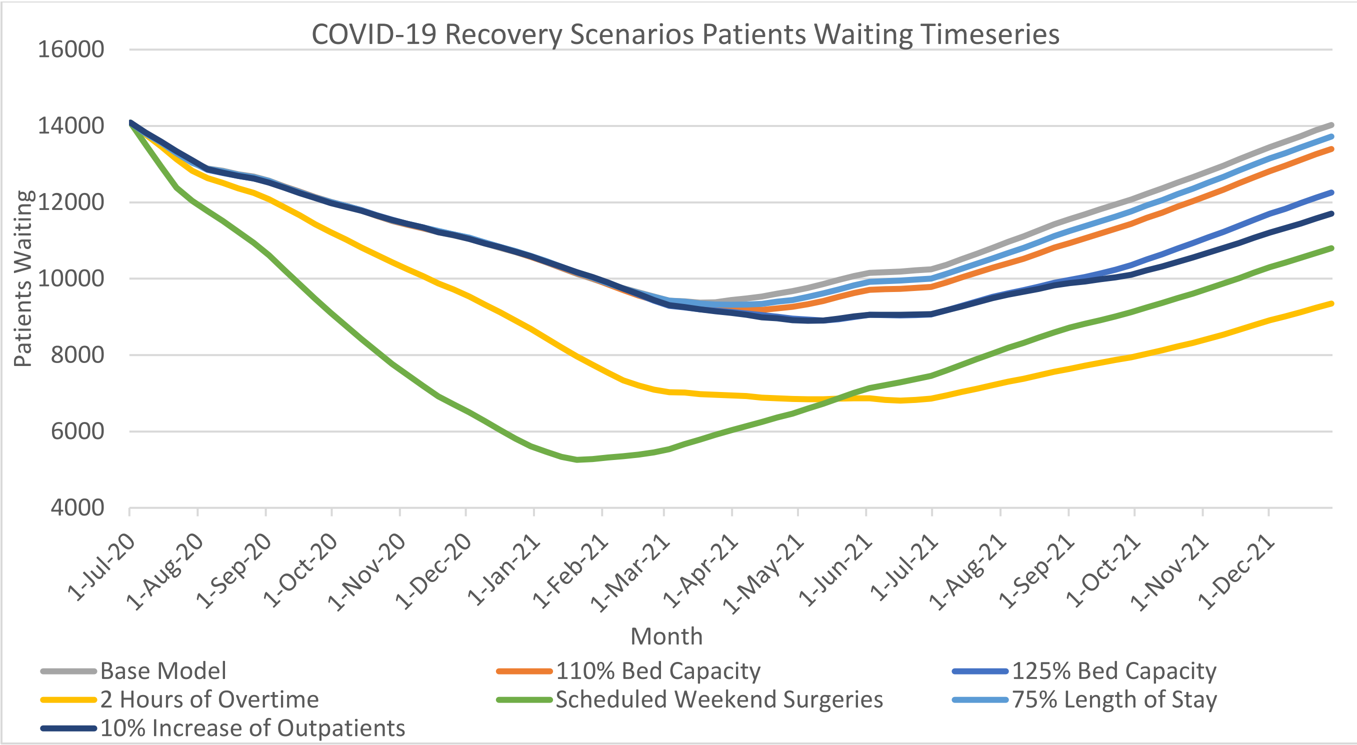

Figure 7.4: COVID-19 Recovery Scenarios Patient Waiting Timeseries

The number of patients waiting at the end of the model run time for each experiment is displayed in Table 7.1 as well as the percent decrease from the base model. Two hours of overtime decreased the patient waitlist by 33%, the largest decrease, and the 75% length of stay scenario decreased the patient waitlist by 2%.

Table 7.1: COVID-19 Recovery Scenarios Results

Experiment	Final Waitlist Length on December 30, 2021	Percent Decrease of Base Model on December 30, 2021
125% Bed Capacity	12,255.5	13%
110% Bed Capacity	13,398.7	4%
2 Hours of Overtime	9,345.9	33%
75% Length of Stay	13,724.1	2%
Scheduled Weekend Surgeries	10,798.8	23%
110% Increase of Outpatients	11,701.7	17%
Base Model	14,025.5	

The slope of November 2021 – December 2021 for each scenario is presented in Table 7.2. The slopes for each scenario represent improvements relative to the base model. The ranked order of the scenarios is identical to the ranked order of the scenarios when analyzing the percent improvement over the base model. This implies that running the model for a longer period would likely not change the rank order of these scenarios. The slope of two hours of overtime is the lowest slope and the 110% bed capacity scenario has the steepest slope. Scheduling weekend surgeries and increasing outpatients by 10% have very similar slopes and follow the two hours of overtime in the ranking.

Table 7.2: Slope For Each Scenario November 2021-December 2021

Scenario	Slope (Patients Waiting/Week)
2 Hours of Overtime	16.4
10% Increase of Outpatients	18.3
Scheduled Weekend Surgeries	18.9
125% Bed Capacity	21.0
75% Length of Stay	21.6
110% Bed Capacity	21.7
Base Model	21.7

The impacts of the scenarios on the individual surgical specialties were not identical. Two examples of the discrepancy in the results are evident in cardiac and general surgery as illustrated in Figure 7.5 and Figure 7.6, respectively. The scenarios have varied impacts on the cardiac waitlist. The scenarios which had similar impacts on the cardiac patient waitlist as the overall patient waitlist were the decreased length of stay, scheduled weekend surgeries, 10% increase of outpatients, and two hours of surgical overtime. However, the increase in the bed capacity curve had different characteristics in the cardiac waitlist than the overall patient waitlist. Overall, like the total patient waitlist, allowing two hours of overtime had the largest impact on the overall cardiac surgical waitlist. This is because cardiac is comprised of longer surgical procedures. Thus, the addition of the two hours of surgery time allows longer surgeries to be scheduled during the day. The impacts of the scenarios on general surgery differ from that of cardiac surgery. At the end of the simulation run time the scenarios fall in same order as the overall patient waitlist. However, the differences in the scenarios are not as extreme as the difference seen in cardiac, as evident in Table 7.3.

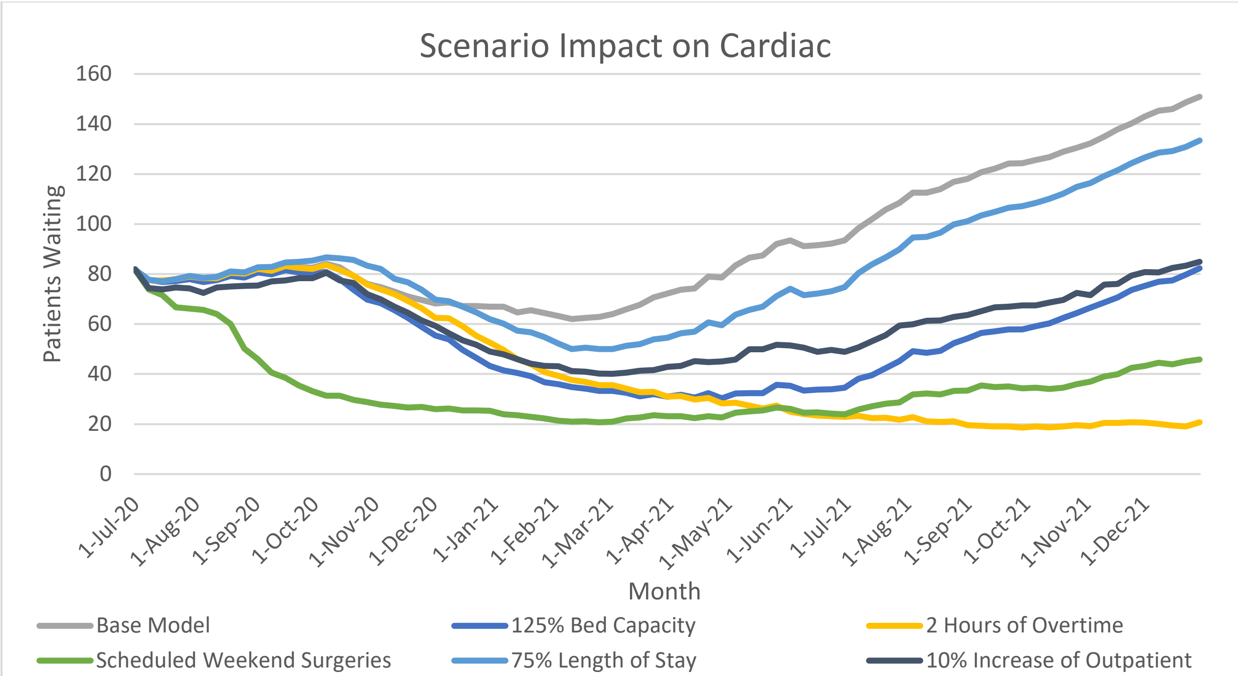

Figure 7.5: Cardiac Patient Waiting Timeseries Impacts of the Scenarios

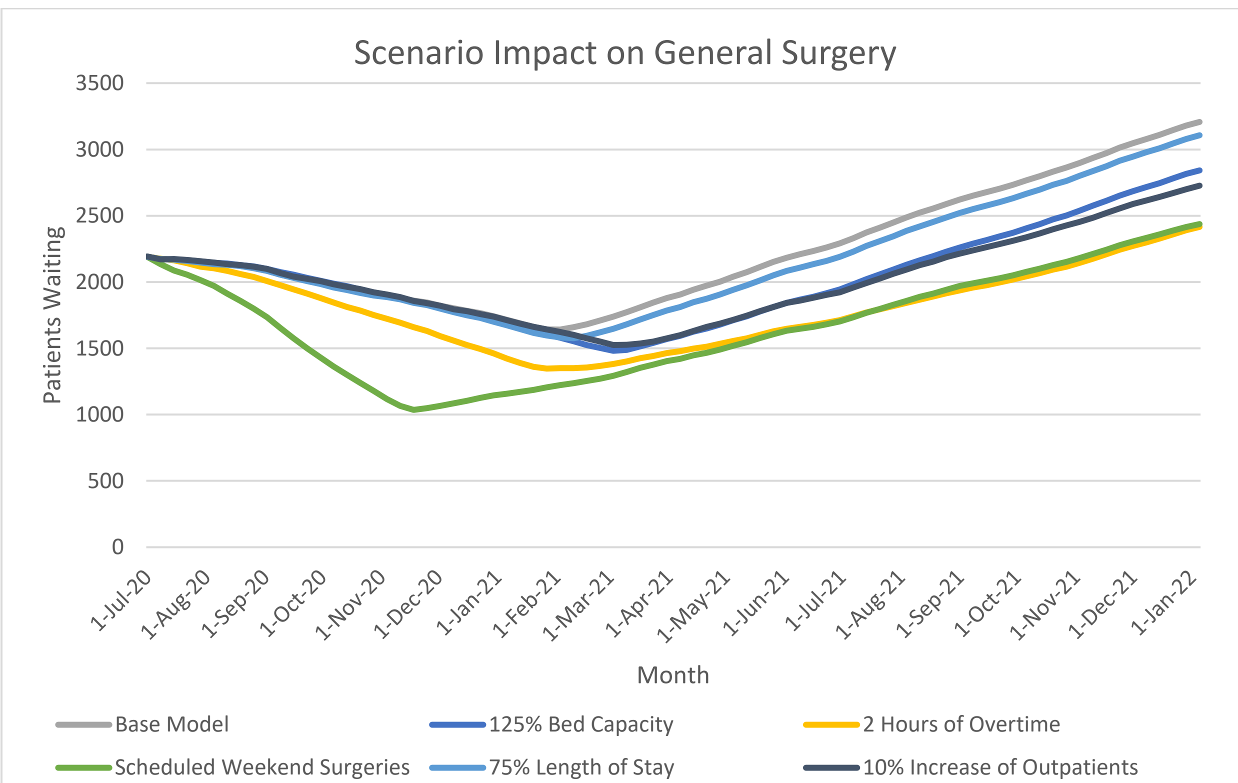

Figure 7.6: General Surgery Patient Waiting Timeseries Impact of Scenarios

Table 7.3: Scenario Percent Difference from Base Model for Cardiology and General Surgery on January 1, 2022

Scenario	Cardiac	General
2 Hours of Overtime	86%	25%
Scheduled Weekend Surgeries	69%	24%
10% Increase of Outpatient	43%	15%
125% Bed Capacity	45%	11%
75% Length of Stay	12%	3%

7.2.2 COVID-19 Effects

The results of the COVID-19 Effects scenarios are illustrated in Figure 7.7. The base model is included as a comparison with the scenarios. The biggest impact is the combination of both the increased cleaning time and demand. The increased cleaning time has an overall effect on the patient waitlist from the beginning and follows the same trend as the base model.

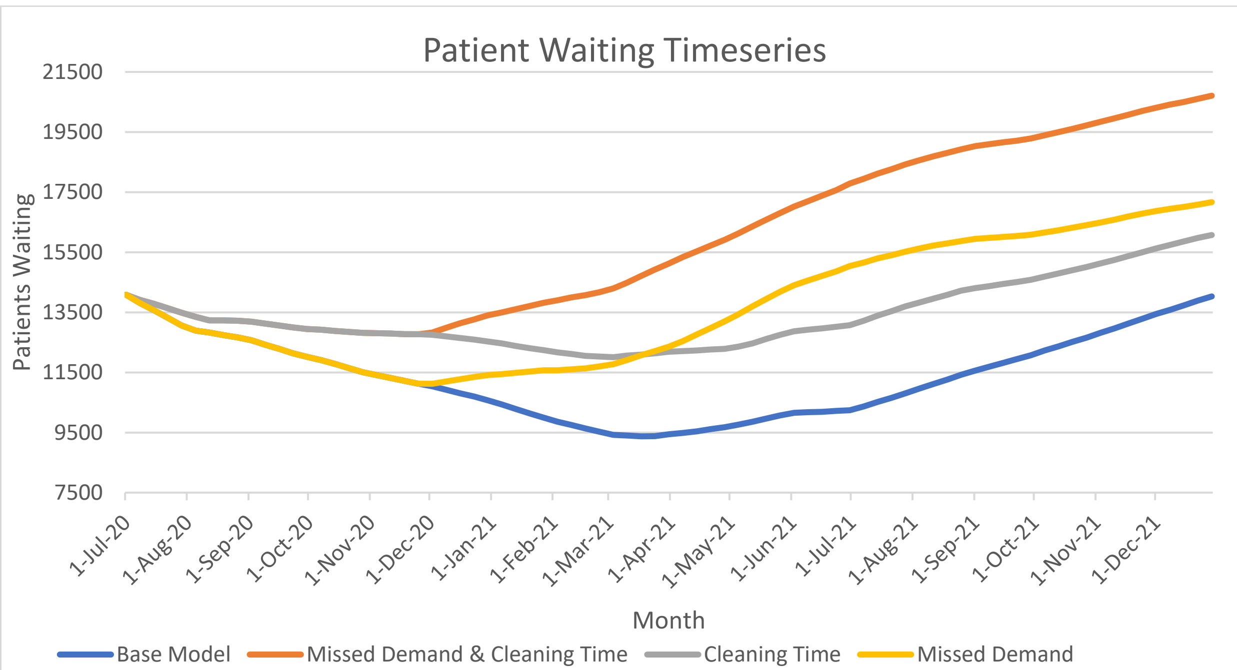

Figure 7.7: Scenarios on the Effects of COVID-19

The number of patients waiting at the end of the model run time for each experiment is displayed in Table 7.2 as well as the percent increase from the base model. Cleaning time results in a 13% increase in the number of patients waiting, there was an 18% increase for the increased demand, and, when the two scenarios were combined, there was a 32% increase in the number of patients on the waitlist.

Table 7.4: COVID-19 Effects Results Comparison

Experiment	Final Waitlist Length on December 30, 2021	Percent Increase of Base Model on December 31, 2021
Cleaning Time	16,073.2	13%
Missed Demand	17,167.8	18%
Missed Demand & Cleaning Time	20,710.9	32%
Base Model	14,025.5	

7.3 Combination of Experiments

There were two experiments that were designed which incorporated two or more previous scenarios. The two experiments were combining the most effective COVID-19 recovery methods and combining the COVID-19 recovery methods with the effects of COVID-19.

7.3.1 Effective COVID-19 Recovery Methods

The two most effective COVID-19 Recovery Methods were 10% increase of outpatients and two hours of operating room overtime. The two methods were combined to determine the impacts of the scenarios on the overall patient waitlist. Figure 7.8 illustrates combining the two scenarios decreases the overall number of patients waiting initially but results in the waitlist beginning to climb at the end of the simulation run.

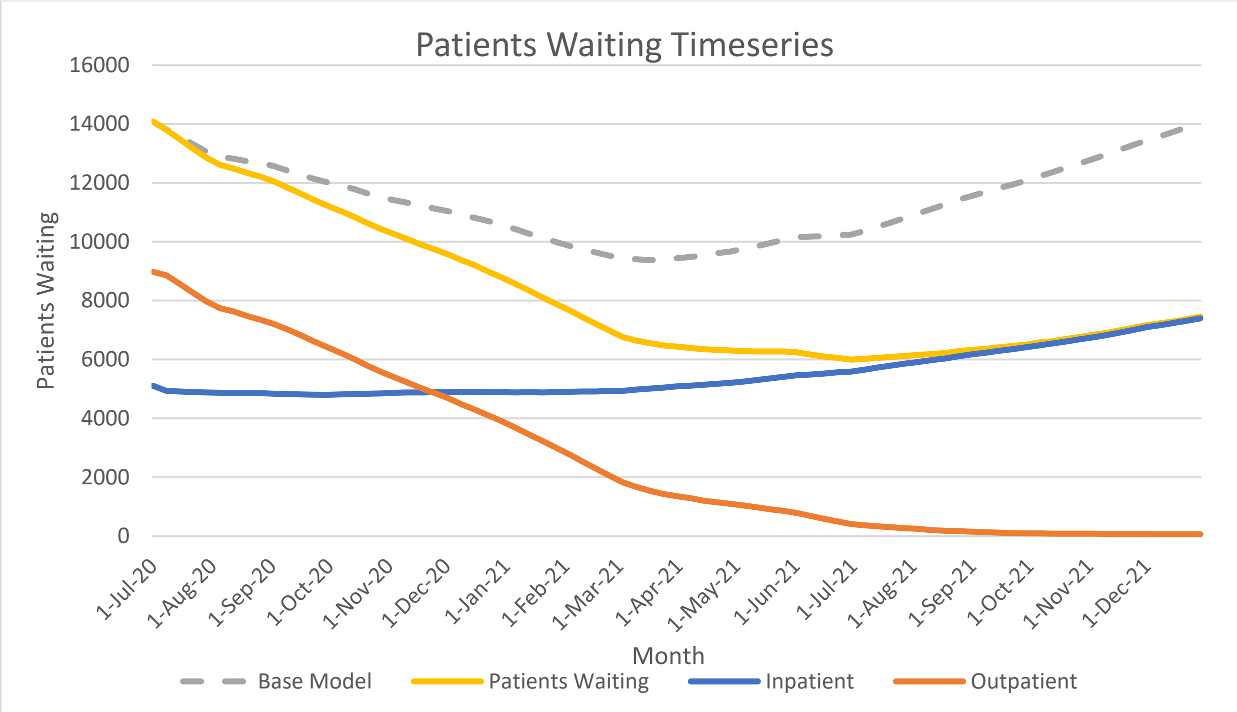

Figure 7.8: Combined COVID-19 Recovery Methods Patient Waiting Timeseries Results

The number of inpatients continues to increase over time in Figure 7.8. Thus, to eliminate the increase of the inpatients over time the 10% increase of outpatients was changed to 50%. The percentage of outpatients and inpatients was increased and decreased by 50%, respectively, for the surgical procedure codes that had both inpatient and outpatients. The second recovery scenario, two hours of operating room over time, was not altered in this experiment. The results are presented in Figure 7.9. The number of inpatients remains at a steady rate with a slight overall decrease that levels off at the end of the simulation run. The number of outpatients on the waitlist continues to decrease over time until the number of inpatients and outpatients meet to continue at a steady rate at the end of the simulation run. The total number of patients on the waitlist continues to decrease over time until the waitlist begins to level out in the final months of the simulation run time.

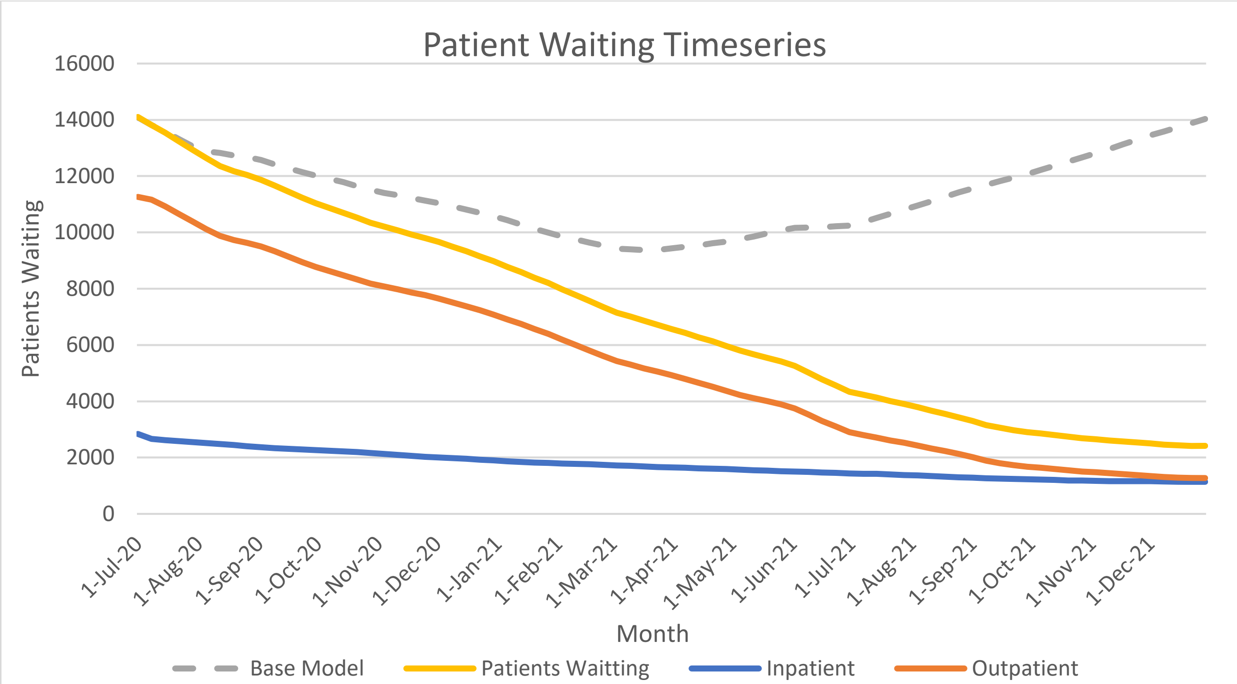

Figure 7.9: Combined COVID-19 Recovery Efforts Patient Waiting Timeseries Results Increased Outpatient

7.3.2 COVID-19 Effects with COVID-19 Recovery Methods

The impacts of the recovery scenarios in the presence of COVID-19 effects are displayed in Table 7.5. Overall, the impact of the recovery methods when COVID-19 effects are added to the model was not as impactful as the effects on the base model.

Table 7.5: Scenario Result Comparison for Demand & Cleaning Time

Scenario	Final Patient Waitlist Length	Base Percent Decrease	Slope
75% Length of Stay	20,097	1%	14.3
2 Hours of Overtime	17,406	14%	9.3
110% Bed Capacity	19,847	2%	14.0
125% Bed Capacity	19,440	4%	13.8
10% Increase of Outpatients	18,715	7%	11.7
Scheduled Weekend Surgeries	15,993	21%	19.7
Demand & Cleaning Time	20,201		

The weekend scheduled surgeries scenario had overall the largest impact during the simulation run time, as displayed in Figure 7.10. However, the slope of the number of patients on the waitlist at the end of the simulation indicates the two hours of over-time is growing at the slowest pace. The scenario that has the second least steep slope is the 10% increase of outpatients.

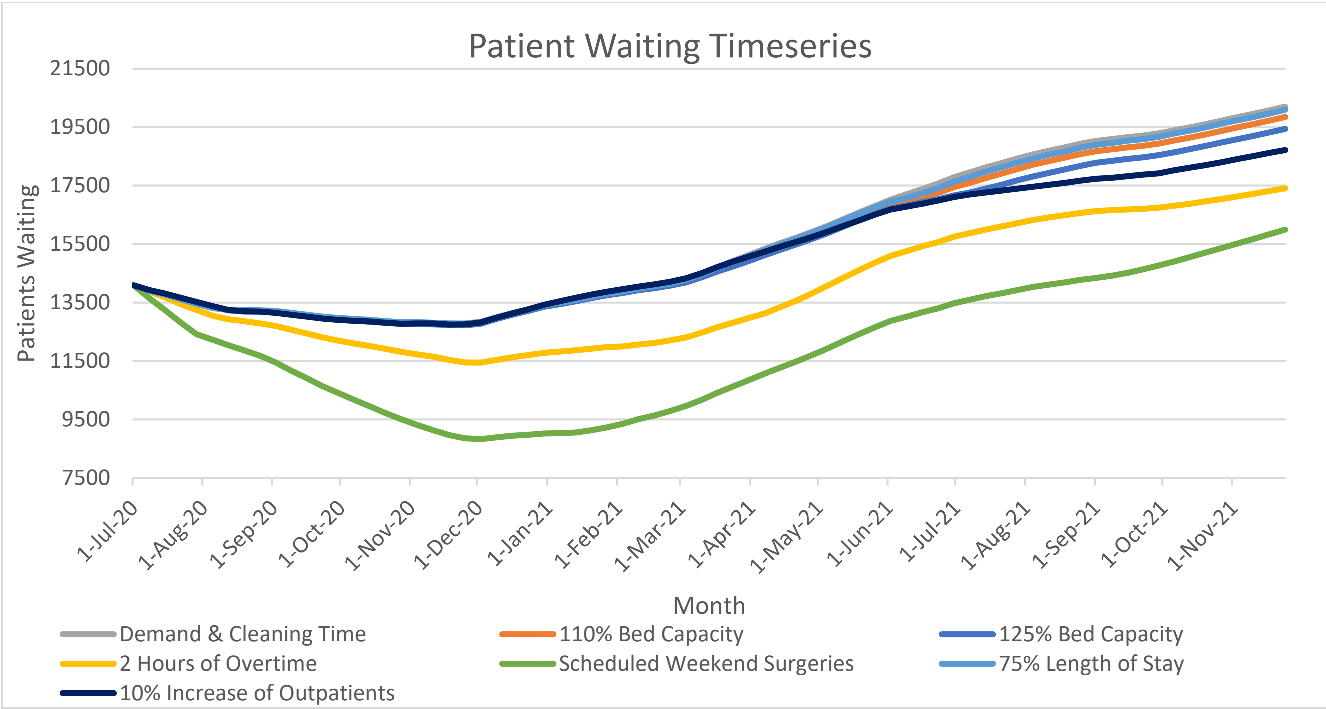

Figure 7.10: COVID-19 Recovery Scenarios Applied to Demand and Cleaning COVID Scenarios

8 Discussion

The base model results indicate the waitlist has an initial decrease and then increases significantly to return (and exceed) the initial waitlist length. The surgical specialties which comprise the majority of the waitlist at the end of the simulation run are general surgery, orthopedic surgery, and urology. This is different from the initial waitlist which is comprised mostly of general surgery, orthopedic surgery, and ophthalmology. The remaining surgical specialties combined comprise 40% of the total waitlist.

The initial decline followed by an increase for the total patient waitlist is due to the proportion of inpatients and outpatients on the waitlist. The inpatient waitlist continues to grow for the entirety of the simulation model run while outpatients decline throughout. Inpatients are routinely blocked from achieving a surgical procedure due to the limited number of beds available. The outpatients are therefore able to fill in the operating room even when there are no recovery beds. This results in the outpatients eventually achieving a steady state in the model. This steady state allows outpatients to enter the system and receive their surgery at the time they enter the waitlist. 90% of procedures within each surgical specialty are majority inpatient procedures, as identified in Table 3.23. Thus, the majority of cases that enter the patient waitlist result in a patient needing a recovery bed. Currently, NSH does not consider the patient status (inpatient vs. outpatient) when scheduling surgical patients. The model presented does not aim to schedule patients in the system; however, it is evident that the scheduling and handling of patients based on the patient status has a large impact on the types of patients receiving surgery. The incorporation of the patient status in the decision process for scheduling surgical patients could improve the use of hospital resources as well as decrease the number of outpatients on the surgical waitlists.

The utilization of the operating rooms is affected by the number of outpatients and inpatients on the waiting list, as shown in Figure 7.3. The utilization of the operating rooms decreases dramatically when the number of outpatients on the waiting list reaches a steady state. The inpatients are not able to utilize the operating rooms due to the limited number of beds, as aforementioned. The downstream resource requirements and the mix of inpatients and outpatients on the waitlist affects the utilization of the operating rooms. An increase to the number of outpatients on the surgical waitlist and scheduling patients based on the downstream resource requirements could increase the operating room utilization. The consideration of the recovery needs of the patients when scheduling would allow patients of both inpatient and outpatient status to move through the system as there is surgical capacity available.

In the recovery strategies outlined by both Ontario Health (2020) and British Columbia Ministry of Health (2020) it was suggested to increase the recovery capacity for surgical services by 15%. It was expected the impact of increasing the bed capacity on the overall throughput of the patients would have a significant effect on the overall patient waitlist. However, a 10% and 25% bed capacity increase did not have a significant effect on the overall patient waitlist length. This is due to the proportion of beds available to the number of inpatients on the waitlist. At the end of the simulation there are approximately 14000 inpatients on the surgical waitlist and 357 recovery beds. The larger impacts were produced from allowing two hours of operating room overtime and decreasing the number of inpatients on the waiting list. Increasing the number of hours the operating room is open each day allows for more surgeries, and longer surgeries, to be scheduled during the day. This allowed the surgical waitlist to decrease at a quicker rate initially and reduced the speed at which the waitlist grew once the number of outpatients reached a steady state.

The sensitivity analysis indicated that bed capacity and patient status have an interaction effect. The interaction effect is evident by the relationship between the beds required and the number of inpatients/outpatients on the surgical waitlist. The increased number of outpatients decreases the number of beds required. The bed constraint remains when the number of outpatients increases as the other constraint on the system is the operating room time. The constraint on the operating room time results in shorter surgical procedures being favored as shorter surgeries can fit within the surgical schedule more easily at any time during the day. The longer procedures are difficult to fit within the schedule unless scheduled at the beginning of the day. Inpatients often have the highest needs and require longer operating room time due to the complexity of the surgery. Thus, inpatients with long surgery times do not move through the system very quickly. The operating room time becomes the constraint in the system when the outpatients reach a steady state as less of the longer inpatient procedures can seize an operating room and move through the system. The bed utilization does not decrease because there are inpatients with short surgical procedures that can continue to obtain surgeries but not enough to fully utilize the operating rooms. The addition of operating room time provides the ability for more of the longer surgical procedures to obtain an operating room. This is evident in the impact of adding operating room time to cardiology, Figure 7.5. Cardiology is comprised mainly of long surgical procedures and the addition of more surgical time had a large impact on the length of the cardiology waitlist. The prioritization of the inpatients with long surgical procedures whilst not allowing outpatients to utilize the majority of the operating room time can improve the utilization of the operating rooms and increase the equality of the rate at which inpatients and outpatients move through the system.

The degree of impact of each of the scenarios on the waitlist for each surgical specialty varied. However, scenarios where collated in the same order for each surgical specialty. It is important to understand the impacts of each scenario on each of the surgical specialties when considering the scenarios for implementation. Although some surgical specialties, such as cardiac surgery, benefit greatly from allowing two hours of overtime another surgical specialty may benefit from the same technique a negligible amount. The implementation of the strategies has impacts on the costs as well as employee satisfaction/burnout which may be greater than the benefit produced by the strategy from the perspective of the health organization.

The scenarios which analyzed the effects of the COVID-19 pandemic through additional cleaning measures as well as increased demand demonstrated the large negative impact of COVID-19 on the surgical waitlist. All of the scenarios increased the patient waitlist. The application of the recovery strategies indicated that recovery efforts will be difficult to create a large impact in an environment with the increased cleaning time and demand. The interaction between the arrival rate and the patient status explains the increase in the patient waitlist with the increased demand. It further explains the reduced benefit of the recovery scenarios because of the increased number of inpatients. However, the scenarios can still produce beneficial results despite the increase. The introduction of weekend surgeries whilst the demand and cleaning time have increased will allow outpatients to continue to flow through the system as well as ensure the inpatient beds are utilized as soon as the beds are available. Long term, however, the weekend surgeries does not decrease the rate at which the surgical waitlist increases. The largest impact on the rate of increase of the surgical waitlist at the end of the simulation is allowing two hours of operating room overtime.

The validity of the model does not discount the presence of limitations. The model results differ from the expected real world implementation. The patients are added and removed from the waitlist in many ways which are not all captured by the model. The model simplifies the addition of patients to the waitlist by smoothing the patients who are added to the waitlist. Further, patients are removed from the waitlist without consideration for the number of beds available. The patients are scheduled for surgery and the hospital works at all costs to ensure the surgery is not cancelled which is not replicated within the model. The basis for the model development was the Nova Scotia healthcare system but can be used for other health authorities and was not tested on other health authorities within Canada or elsewhere. Lastly, the number of distributions fit to the data do not provide an understanding of the overall behavior of the length of stay and the surgery length for each procedure code. The fit of the distributions developed may be too fitted to the data and allowing for less distributions would provide more variability to be incorporated whilst still accurately representing the data.

There are future research opportunities available in reference to the research conducted. An opportunity exists to quantify the impact of the outlined strategies in conjunction with surgical scheduling strategies. This includes scheduling patients using a method that considers the utilization of downstream resources and the case mix of the patient waitlist. An analysis of the constraints within the system, how the constraints change as the case mix changes, and the impacts of the scheduling on the constraints would ameliorate the scheduling analysis. The work can be expanded to incorporate the entire province of Nova Scotia. This would allow an understanding of the intricacies of the region to be incorporated and identify areas where resource allocation can have a different impact. Further, the incorporation of patient outcomes in relation to completing surgical procedures as a method to sort the queue in conjunction with the priority of the patients on the waitlist would facilitate an understanding of how to address the more elective procedures on the waitlist. Lastly, the incorporation of more aspects of the hospital environment to account for the intricate nature of a healthcare environment would provide a more holistic overview of the impacts of the selected scenarios.

9 Conclusions

The focus of the research was to analyze the impacts of resource allocation and demand on the patient waitlist over time. The interpretation of the results aims to support the development of strategies to address the surgical backlog created by the COVID-19 pandemic.

The research contributed the descriptive analytics of the surgical data provided by NSH. The analysis of the data facilitated the development of the model and identified the components of the surgical system. The data also provided an understanding of the current use of the system with respect to the operating room utilization, waitlist case mix, and renege rate of the surgical specialties. The results of the data analysis illustrated the true operations of the surgical departments as well as the characteristics of the current waitlist case mix. This provides valuable information to the surgical department to aid in the development of operational strategies.

The second, and main, contribution of the thesis is the simulation model developed using model parameters and inputs obtained from the descriptive analytics as well as discussions with subject matter experts. The analysis of the simulation model developed provided a novel approach to the surgical backlog created by COVID-19. The model aligned with previous research in the methodology; however, the patient waiting metric was uncommon in previous research. The results of the simulation model identified the interaction between the number of outpatients and inpatients on the surgical waitlist and the utilization of the operating rooms. The case mix of the surgical waitlist is an important component of the time it takes to reduce the patient waitlist. However, currently the patient status is not accounted for when scheduling surgical patients. The addition of operating room time allowed the surgical waitlist to significantly decrease at the beginning of the simulation run. The addition of surgical time allows the outpatients to move through the system at a faster rate and allows for longer inpatient procedures to occur. This allows the movement of the inpatients and outpatients to be more equitable on the patient waitlist. The impacts of COVID-19 on the surgical environment, increased cleaning time and demand, resulted in a large increase in the overall length of the patient waitlist. The recovery methods were less effective in the COVID-19 environment. However, increasing the number of operating room hours available provides the largest impact on the patient waitlist.

The structure of the model facilitates the transferability of the model to other hospitals or health authorities. The pandemic experience in Nova Scotia has been unique compared to other provinces and countries. This was considered during the model development to facilitate variation in the scope of studied facilities as well as the scenarios. Additionally, the model can be used to address the surgical waitlist outside of COVID-19 during, what was previously known as, normal times. The model can provide effective identification of resource allocation strategies to address the surgical backlog created by COVID-19 as well as the already well documented long waitlists in the surgery department.

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Appendix A

The operating room schedule at the Victoria General Hospital is displayed in Table A.0.1.

Table A.0.1: Victoria General Hospital Operating Room Schedule Data

Day	OPDS-17	OPDS-18	OPDS-19	OPDS-20	VG10-09	VG10-10	VG10-11	VG10-12	VG10-13
Sunday	2.0	0.0	2.0	0.0	0.0	2.0	0.0	3.0	2.0
Monday	7.0	7.0	7.0	7.0	0.0	8.0	8.0	9.0	9.0
Tuesday	7.0	7.0	7.0	7.0	0.0	8.0	9.0	7.0	9.0
Wednesday	7.0	7.0	7.0	7.0	0.0	7.0	7.0	8.0	7.0
Thursday	7.0	7.0	7.0	7.0	1.0	8.0	8.0	9.0	9.0
Friday	7.0	7.0	7.0	7.0	0.0	8.0	8.0	8.0	9.0
Saturday	0.0	3.0	0.0	0.0	0.0	0.0	3.0	3.0	3.0
Total	**6.0**	**18.0**	**4.0**	**1.0**	**1.0**	**41.0**	**43.0**	**47.0**	**48.0**
Day	VG10-15	VG10-16	VG11-01	VG11-03	VG11-04	VG11-05	VG11-06	VG11-07	VG11-08
Sunday	5.0	3.0	4.0	4.0	0.0	3.0	4.0	4.0	4.0
Monday	8.0	6.0	7.0	7.0	2.0	4.0	5.0	8.0	8.0
Tuesday	9.0	5.0	7.0	7.0	3.0	4.0	5.0	9.0	8.0
Wednesday	9.0	5.0	6.0	5.0	3.0	4.0	6.0	10.0	8.0
Thursday	8.0	6.0	7.0	6.0	3.0	4.0	6.0	9.0	8.0
Friday	8.0	5.0	6.0	6.0	3.0	4.0	9.0	9.0	8.0
Saturday	5.0	3.0	4.0	5.0	0.0	3.0	5.0	4.0	4.0
Total	**52.0**	**33.0**	**41.0**	**40.0**	**14.0**	**26.0**	**40.0**	**53.0**	**48.0**

Table A.2 illustrates the number of times each operating room was open on each weekend for the two year period.

Table A.2: Victoria General Hospital Operating Room Weekend Use

	2018			2019		
	Saturday	Sunday	Weekend	Saturday	Sunday	Weekend
VG11- 08	10	10	10	12	11	12
VG10-16	12	12	12	12	12	12
VG10-15	12	11	12	12	11	12
VG11- 01	11	11	11	11	11	11
OPDS- 19	11	9	10	12	9	11

The amount of time provided to each surgical specialty at Victoria General Hospital is illustrated in Table A.0.3.

Table A.0.3: Victoria General Hospital Operating Room Time Distribution for Surgical Specialty

Room	GEN	OBGYN	OMFD	OPHTH	OTOL	THOS	URO
OPDS- 17	0.0	0.0	0.0	6.0	0.0	0.0	0.0
OPDS- 18	0.0	0.0	0.0	18.0	0.0	0.0	0.0
OPDS- 19	0.0	0.0	0.0	4.0	0.0	0.0	0.0
OPDS- 20	0.0	0.0	0.0	1.0	0.0	0.0	0.0
VG10-09	0.0	0.0	1.0	0.0	0.0	0.0	0.0
VG10-10	0.0	0.0	0.0	0.0	0.0	0.0	41.0
VG10-11	0.0	0.0	0.0	0.0	0.0	0.0	43.0
VG10-12	0.0	0.0	0.0	0.0	0.0	0.0	47.0
VG10-13	0.0	0.0	0.0	0.0	0.0	0.0	48.0
VG10-15	0.0	0.0	0.0	0.0	0.0	0.0	52.0
VG10-16	0.0	0.0	0.0	0.0	0.0	0.0	33.0
VG11- 01	41.0	0.0	0.0	0.0	0.0	0.0	0.0
VG11- 03	17.4	22.6	0.0	0.0	0.0	0.0	0.0
VG11- 04	0.0	0.0	0.0	0.0	13.9	0.0	0.0
VG11- 05	0.0	0.0	0.0	0.0	26.0	0.0	0.0
VG11- 06	40.0	0.0	0.0	0.0	0.0	0.0	0.0
VG11- 07	53.0	0.0	0.0	0.0	0.0	0.0	0.0
VG11- 08	0.0	0.0	0.0	0.0	0.0	48.0	0.0
Total	151.4	22.6	1.0	29.0	39.9	48.0	266.0

The operating room schedule at the Halifax Infirmary is displayed in Table A.0.4.

Table A.0.4: Halifax Infirmary Operating Room Schedule Data

Day	HIOR01	HIOR02	HIOR03	HIOR04	HIOR05	HIOR06	HIOR07	HIOR08	HIOR09	HIOR10
Sunday	5.00	4.00	4.00	7.00	4.00	9.00	4.00	3.00	6.00	5.00
Monday	9.00	10.00	9.00	9.00	8.00	11.00	9.00	8.00	11.00	4.00
Tuesday	9.00	10.00	9.00	9.00	9.00	12.00	9.00	9.00	10.00	4.00
Wednesday	8.00	10.00	8.00	9.00	8.00	11.00	9.00	7.00	8.00	5.00
Thursday	11.00	10.00	9.00	10.00	9.00	12.00	9.00	8.00	11.00	4.00
Friday	9.00	9.00	8.00	9.00	9.00	12.00	10.00	6.00	10.00	4.00
Saturday	5.00	4.00	3.00	8.00	4.00	9.00	4.00	4.00	7.00	5.00
Total	**56.00**	**57.00**	**50.00**	**61.00**	**51.00**	**76.00**	**54.00**	**45.00**	**63.00**	**31.00**

Day	HIOR11	HIOR12	HIOR13	HIOR14	HIOR15	HIOR16	HIOR17	HIOR18	HIOR19
Sunday	3.00	0.00	7.00	7.00	4.00	5.00	7.00	6.00	0.00
Monday	0.00	0.00	12.00	11.00	8.00	11.00	9.00	12.00	9.00
Tuesday	3.00	0.00	10.00	11.00	7.00	10.00	9.00	10.00	6.00
Wednesday	5.00	0.00	11.00	11.00	8.00	10.00	8.00	10.00	8.00
Thursday	3.00	7.00	12.00	11.00	8.00	10.00	9.00	13.00	7.00
Friday	3.00	0.00	12.00	11.00	8.00	10.00	8.00	11.00	7.00
Saturday	0.00	0.00	7.00	8.00	4.00	5.00	6.00	6.00	7.00
Total	**17.00**	**7.00**	**71.00**	**70.00**	**47.00**	**61.00**	**56.00**	**68.00**	**44.00**

Table A.5 illustrates the number of times each operating room was open on each weekend for the two year period.

Table A.5: Halifax Infirmary Operating Room Weekend Use

	2018			2019		
	Saturday	Sunday	Weekend	Saturday	Sunday	Weekend
HIOR- 04	12	12	12	12	12	12
HIOR- 05	12	11	12	11	12	12
HIOR- 06	12	12	12	12	12	12
HIOR- 07	12	11	12	12	11	12
HIOR- 18	12	12	12	12	12	12
HIOR- 13	11	12	12	11	10	11
HIOR- 14	12	11	12	10	12	11

The amount of time provided to each surgical specialty at Halifax Infirmary is illustrated in Table A.6.

Table A.6: Halifax Infirmary Operating Room Time Distribution for Surgical Specialty

Room	CARD	GEN	NEURO	ORTHO	PLAS	VAS
HIOR- 01	0	0	23	33	0	0
HIOR- 02	0	0	0	57	0	0
HIOR- 03	0	0	1	49	0	0
HIOR- 04	0	0	0	61	0	0
HIOR- 05	0	0	0	51	0	0
HIOR- 06	0	76	0	0	0	0
HIOR- 07	0	0	0	24	30	0
HIOR- 08	0	0	0	22	23	0
HIOR- 09	0	0	63	0	0	0
HIOR- 10	0	0	0	0	0	31
HIOR- 11	0	0	0	0	0	17
HIOR- 12	0	0	0	0	0	0
HIOR- 13	0	0	71	0	0	0
HIOR- 14	70	0	0	0	0	0
HIOR- 15	47	0	0	0	0	0
HIOR- 16	61	0	0	0	0	0
HIOR- 17	0	0	0	37	0	19
HIOR- 18	0	0	0	0	0	68
HIOR- 19	0	0	0	44	0	0
Total	178	76	158	379	52	135

The operating room schedule at the Scotia Surgery is displayed in Table A.7.

Table A.7: Scotia Surgery Operating Room Schedule Data

Day	SSI-01	SSI-02
Monday	9.0	8.0
Tuesday	8.0	9.0
Wednesday	8.0	7.0
Thursday	9.0	9.0
Friday	8.0	0.0
Total	42.0	33.0

The amount of time provided to each surgical specialty at Scotia Surgery is illustrated in Table A.8.

Table A.8: Scotia Surgery Operating Room Time Distribution for Surgical Specialty

Room	GEN	ORTHO	PLAS
SSI-01	1.5	39.9	0.6
SSI-02	9.0	24.0	0.0
Total	**10.5**	**63.9**	**0.6**

The operating room schedule at the Hants County Hospital is displayed in Table A.9.

Table A.9: Hants County Operating Room Schedule Data

Day	HOR -01	HOR -02	R-HACRMS
Sunday	0	0	0
Monday	7	7	0
Tuesday	7	8	0
Wednesday	8	7	0
Thursday	6	7	3
Friday	7	8	0
Saturday	0	0	0
Total	35.0	37.0	3.0

The amount of time provided to each surgical specialty at Scotia Surgery is illustrated in Table A.10.

Table A.10: Hants County Hospital Operating Room Time Distribution for Surgical Specialty

Room	GEN	OMFD	OPHTH	ORTHO	OTOL	PLAS	VAS
HOR- 01	19.7	1.7	0.1	5.8	5.7	0.3	1.7
HOR- 02	0.0	0.0	34.3	0.3	0.6	0.0	37.0
R-HACRMS	0.0	0.0	0.0	3.0	0.0	0.0	0.0
Total	**19.7**	**1.7**	**34.4**	**9.1**	**6.3**	**0.3**	**38.7**

Appendix B

The utilization of the operating room per week was calculated for the duration of the simulation model. The following Figures present the remaining surgical specialties. The primary y-axis (left) is the operating room utilization per week and the secondary y-axis (right) is the number of patients waiting per week.

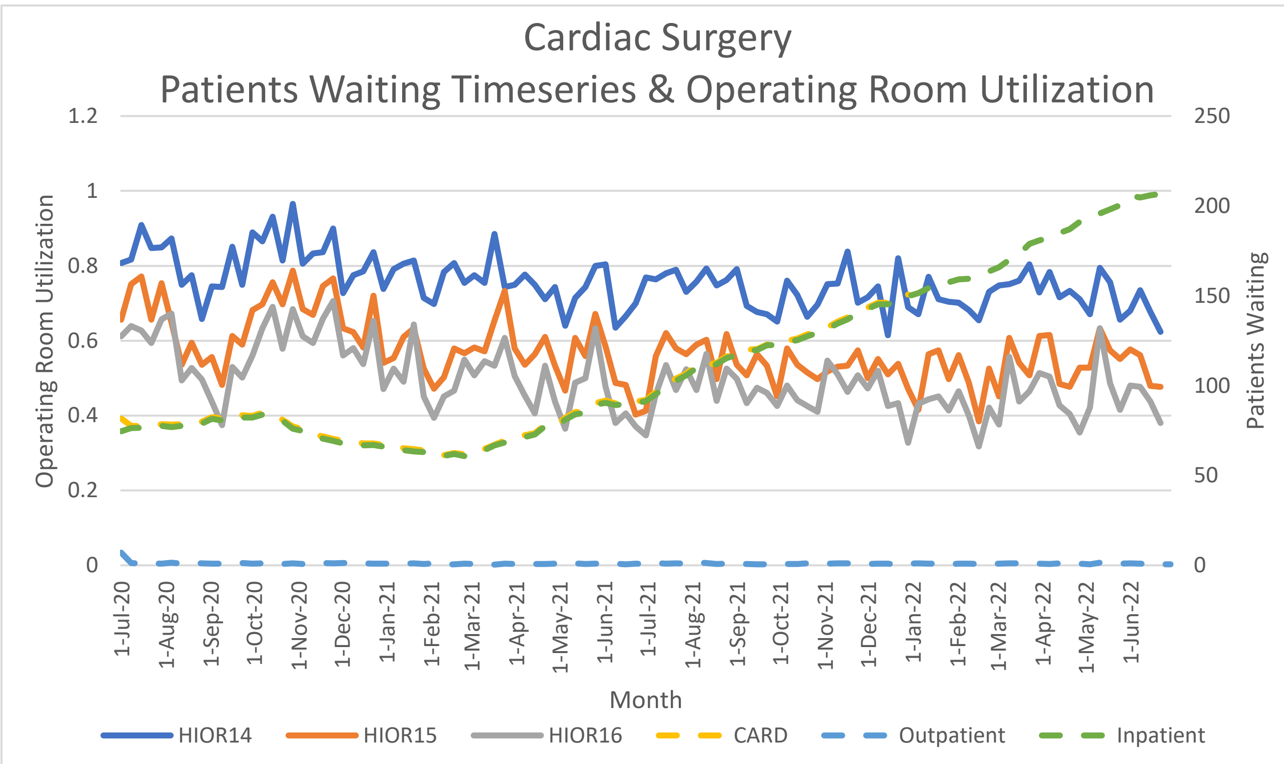


Figure B.0.1: Cardiac Surgery Patients Waiting Timeseries & Operating Room Utilization

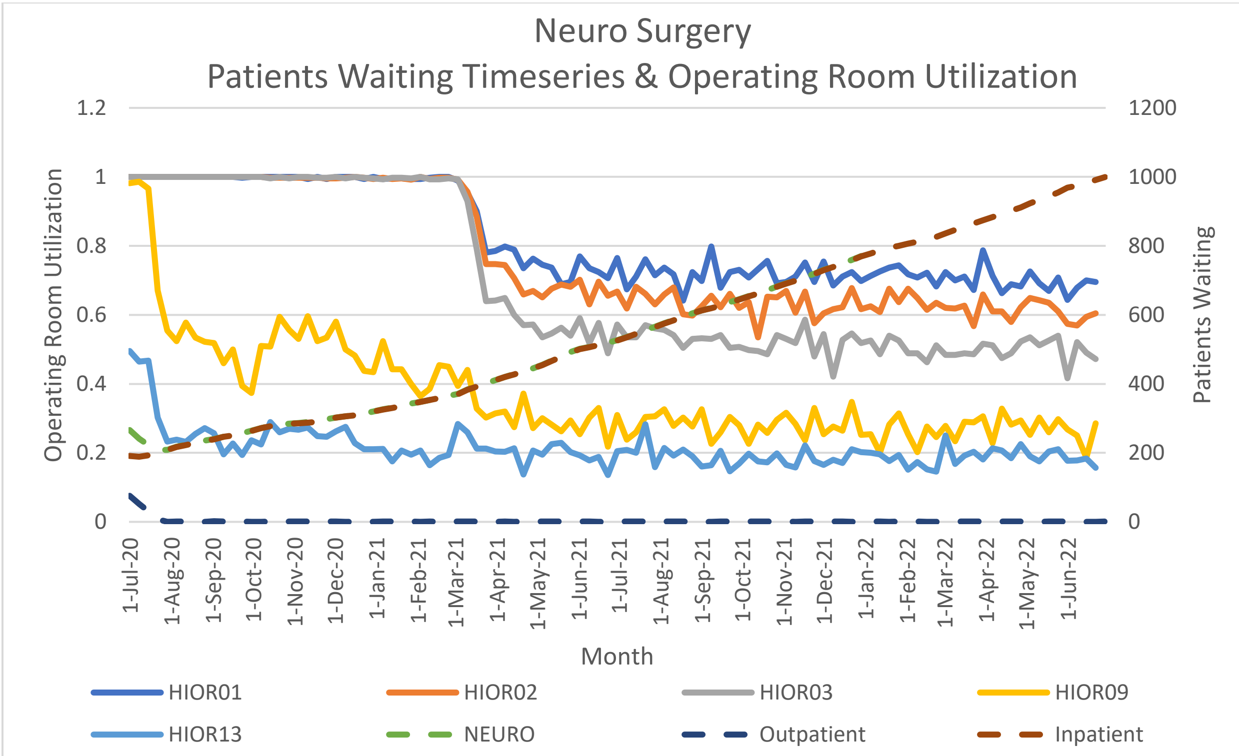


Figure B.0.2: Neuro Surgery Patients Waiting Timeseries & Operating Room Utilization

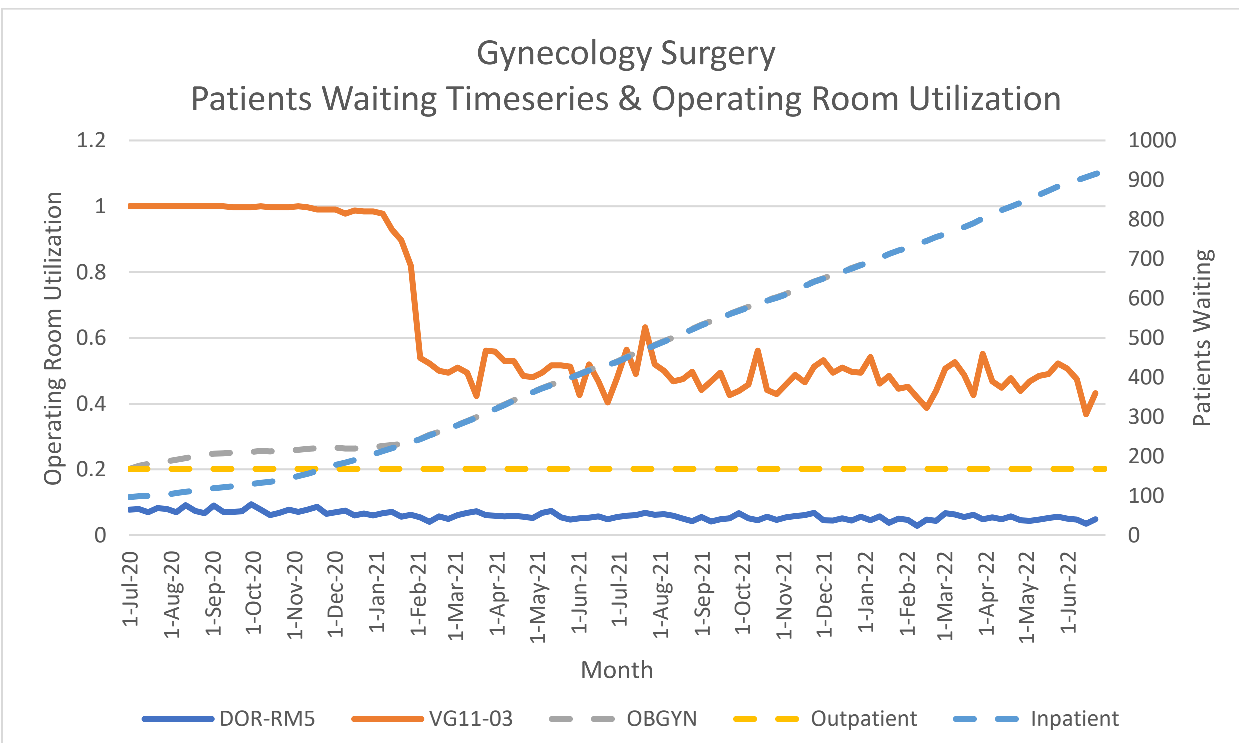


Figure B.0.3:Gynecology Surgery Patients Waiting Timeseries & Operating Room Utilization

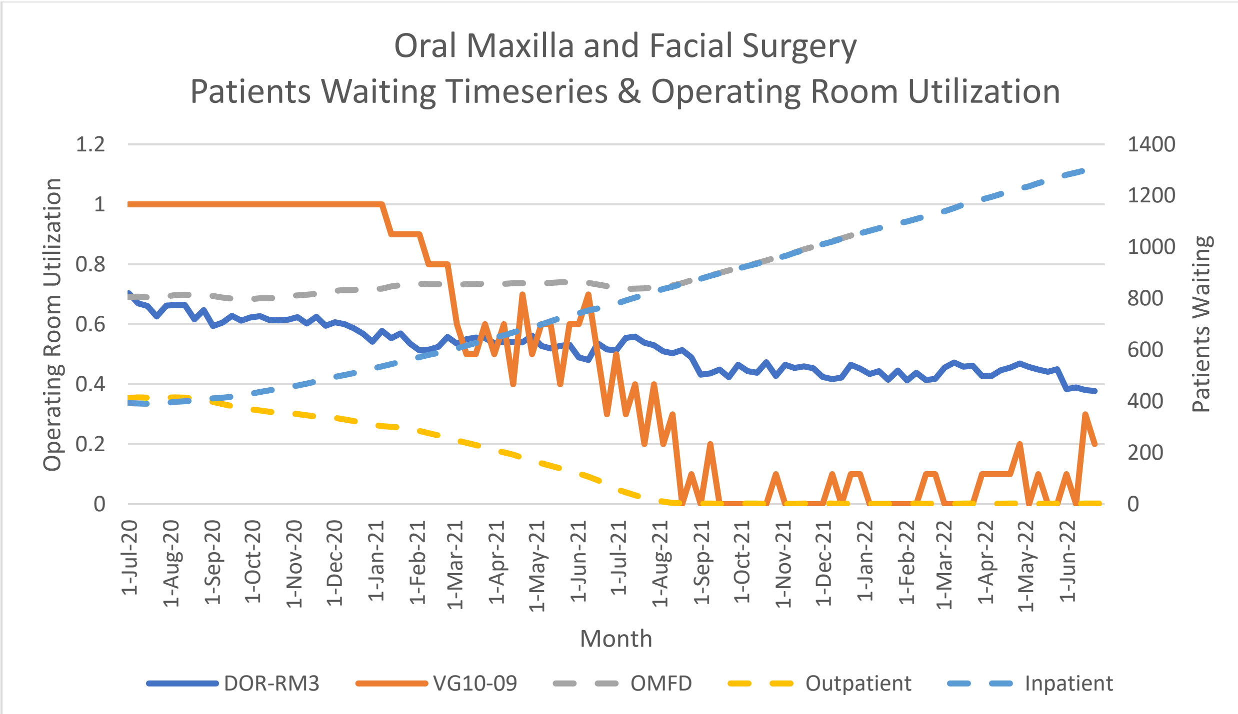


Figure B.0.4: Oral Maxilla and Facial Surgery Patients Waiting Timeseries & Operating Room Utilization

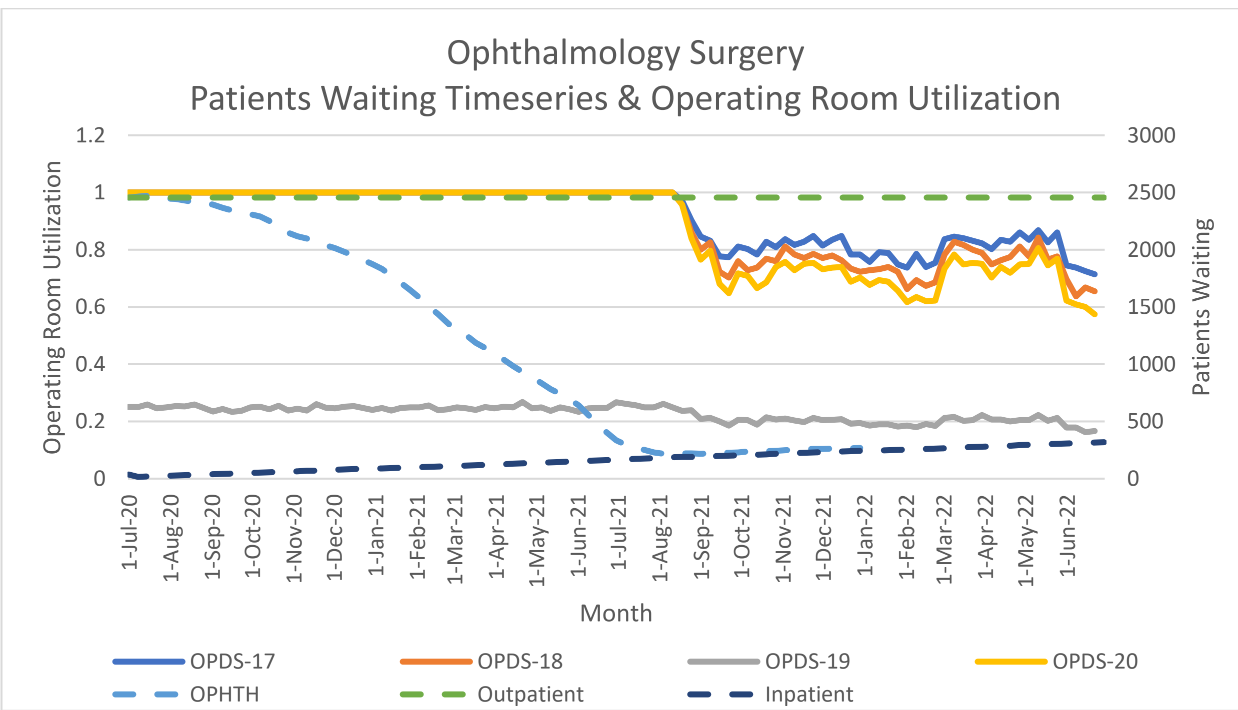


Figure B.0.5: Ophthalmology Surgery Patients Waiting Timeseries & Operating Room Utilization

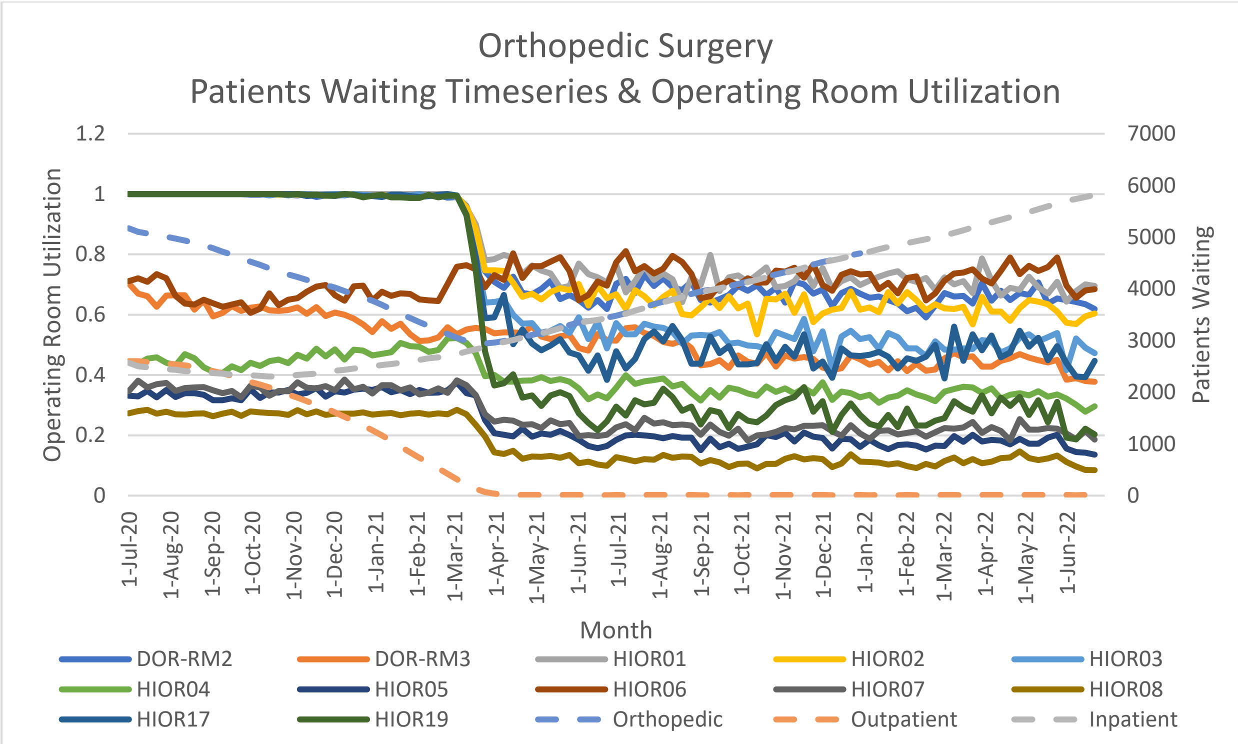


Figure B.0.6: Orthopedic Surgery Patients Waiting Timeseries & Operating Room Utilization

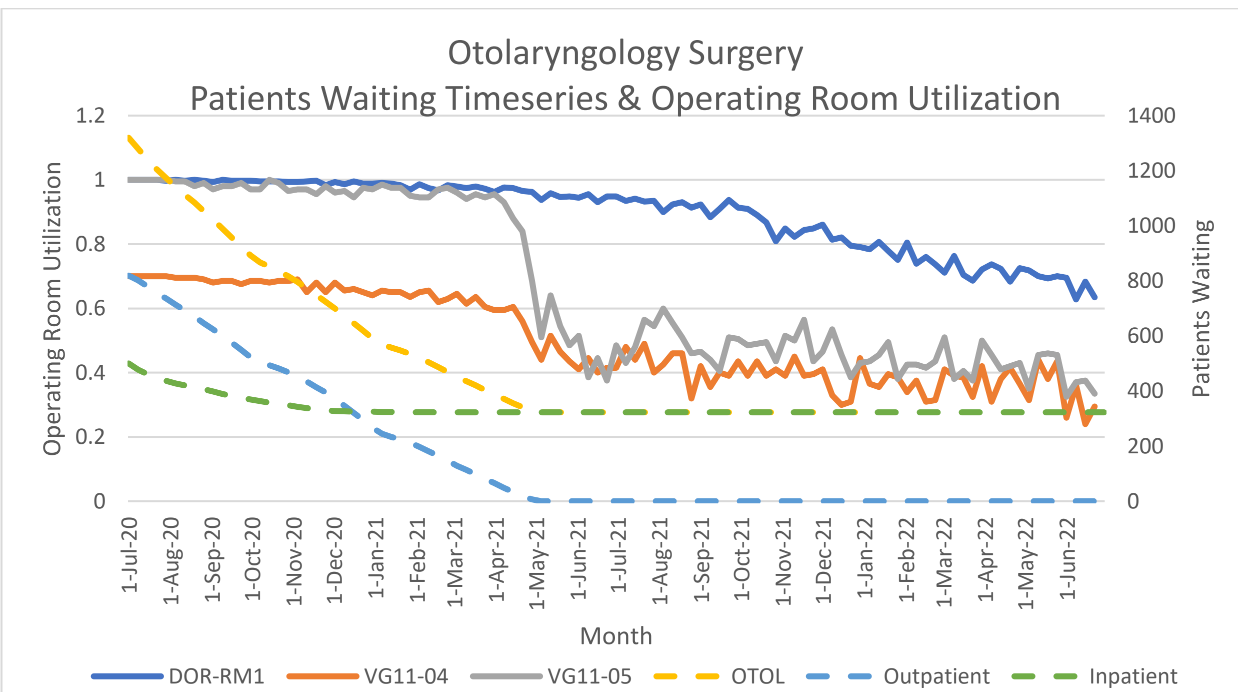


Figure B.0.7: Otolaryngology Surgery Patients Waiting Timeseries & Operating Room Utilization

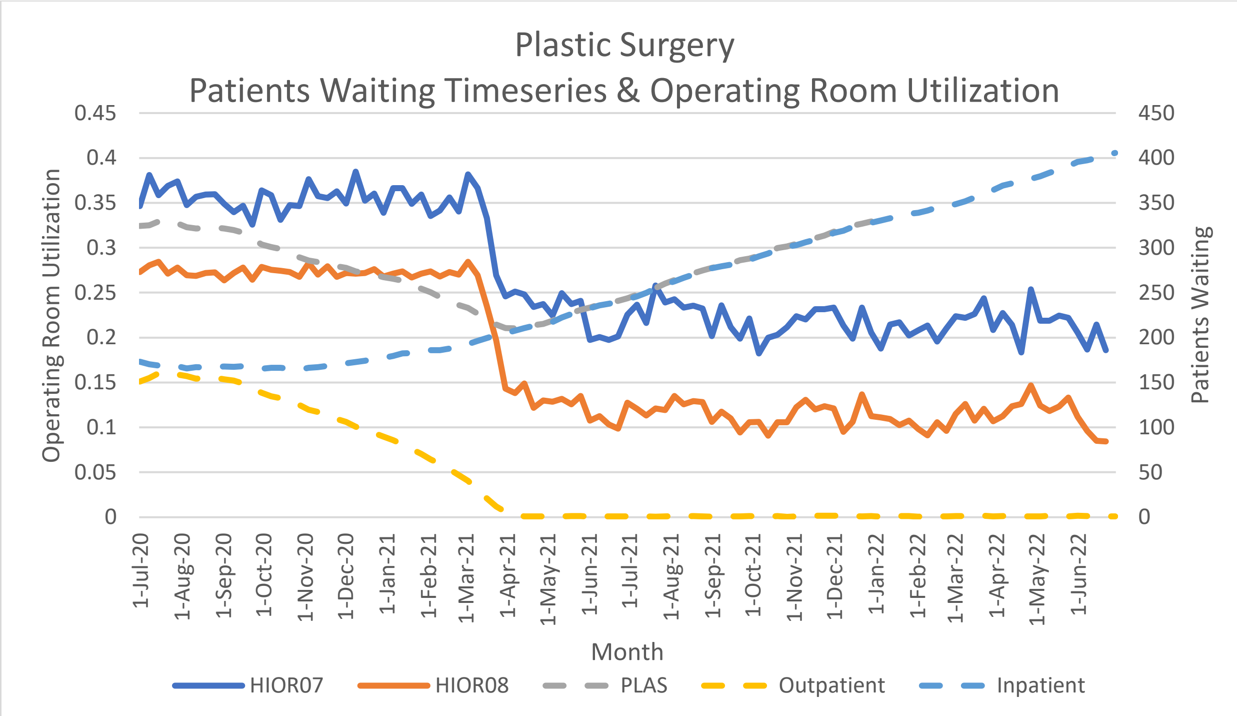
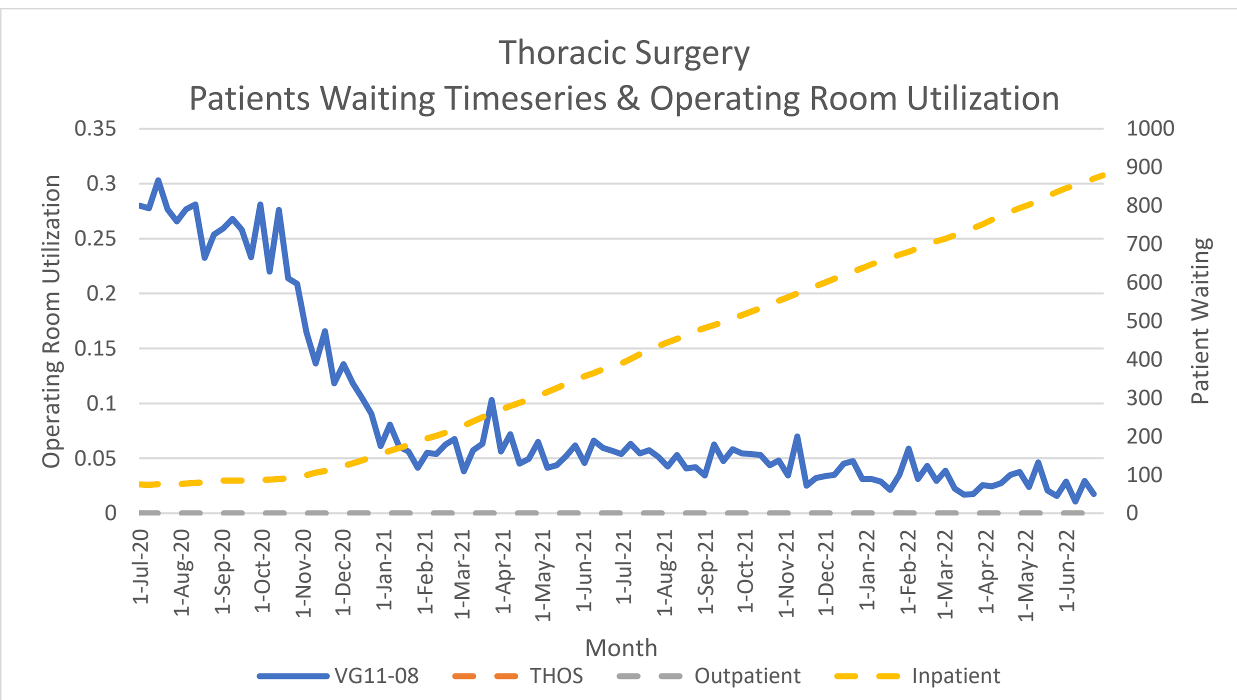


Figure B.0.8: Plastic Surgery Patients Waiting Timeseries & Operating Room Utilization



FigureB.0.9: Thoracic Surgery Patients Waiting Timeseries & Operating Room Utilization

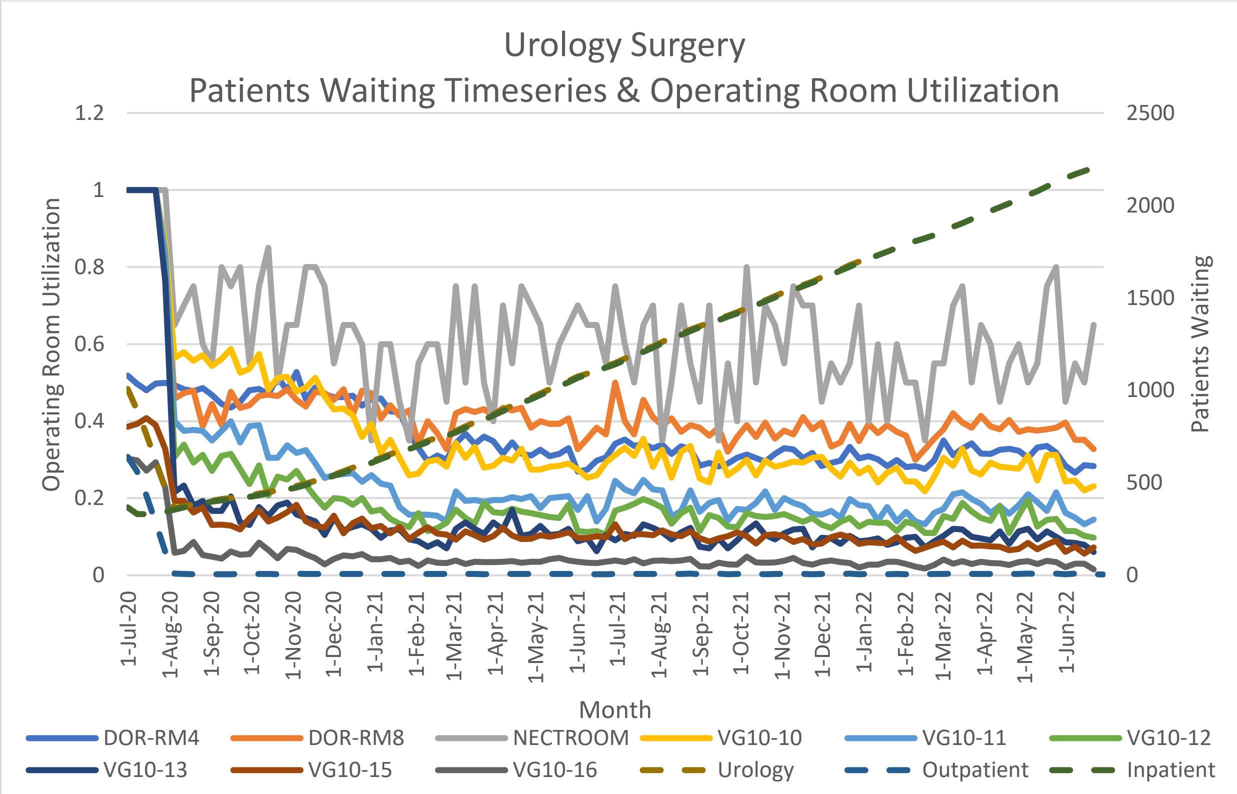


Figure B.0.10: Urology Surgery Patients Waiting Timeseries & Operating Room Utilization

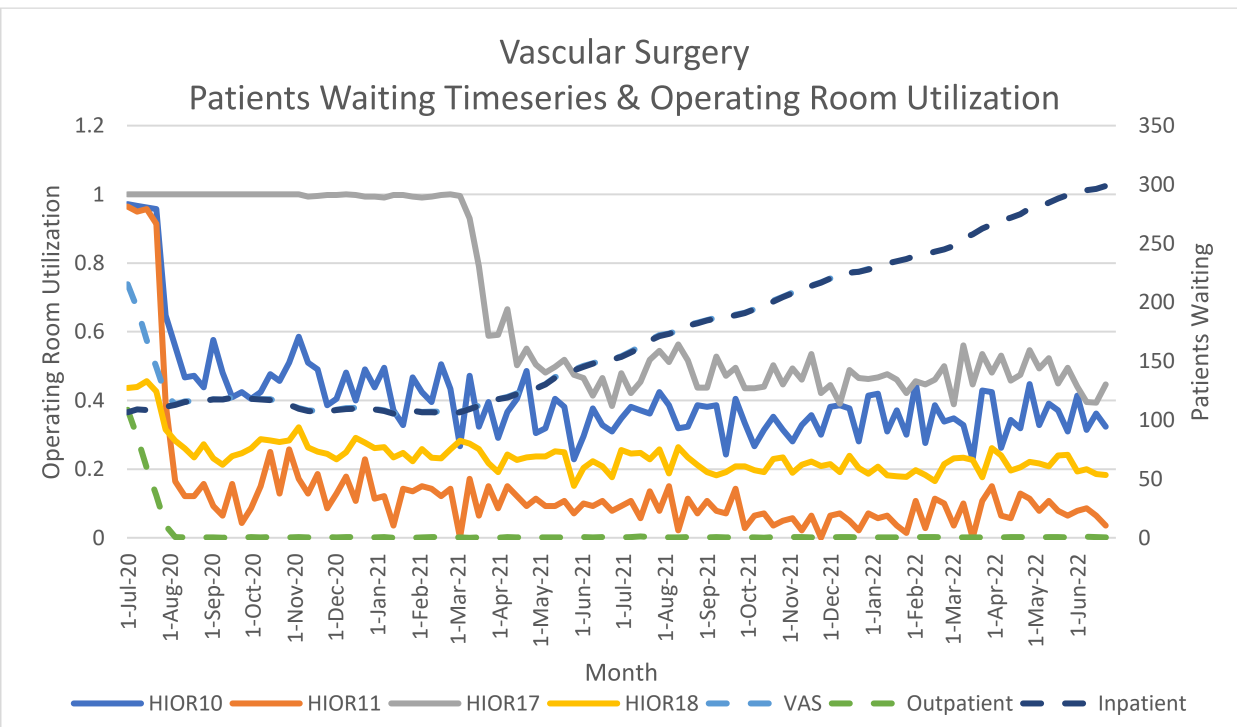


Figure B.0.11: Vascular Surgery Patients Waiting Timeseries & Operating Room Utilization