Implications of Non-Operating Room Anesthesia Policy for Operating Room Efficiency

Yihang Liang

Submitted in partial fulfilment of

the requirements for the degree of

Master of Science in Management

(Operations and Information Systems Management)

Goodman School of Business, Brock University

St. Catharines, Ontario

Abstract

This thesis focuses on examining the use of Non-Operating Room Anesthesia (NORA) policy in Operating Room (OR) scheduling. A NORA policy involves a practice whereby the administration of anesthesia stage is performed outside the OR. The goal of the thesis is to determine whether NORA policy can improve OR efficiency measured by the performance of total costs, which consists of a weighted sum of patient waiting time, OR overtime and idle time. A simulation optimization method is adopted to find near-optimal schedules for elective surgeries in an outpatient setting. The results of a traditional OR scheduling model, where all stages of the surgery are performed in the OR, will be compared to the results of a NORA OR model where the initial anesthesia stage is performed outside of the OR. Two cases are considered for the NORA model given the decrease on mean durations: (1) a model with the same number of surgery appointments and shorter session length and (2) a models with the same session length and more surgery appointments. . The impact of a NORA policy on OR performance is further analyzed by considering scenarios that capture Surgery duration variability and mean surgery durations which are two traits for surgeries that have been shown to impact OR performance. This thesis aims to investigate how a NORA policy performs when standard deviations and mean surgery durations change. The results show that NORA policy can improve OR efficiency in all settings.

Keywords: operating room scheduling, NORA, simulation optimization

Acknowledgements

I would like to thank my supervisor, Dr. Reena Yoogalingam, for her patience and mentorship. I am so grateful for her continuous support and instant feedback. I cannot finish this thesis without her excellent guidance.

I would like to thank my thesis committee members, Dr. Anteneh Ayanso and Dr. Martin Kusy. Their ideas and comments are invaluable for the improvement of my thesis.

I would like to thank my friends, Sihan Wang, Junhui Feng, Qingyi Xu, Sixuan Zhou and Zhiying He for their help through this hard COVID period.

Finally, I would like to thank my parents for their financial and spiritual support. They are the reason for who I am now.

Table of Contents

List of Tables

List of Figures

1 Introduction

1.1 Background

Health spending in Canada was $253.5 billion in 2018, which represents 11.3% of Canada's gross domestic product. Hospital expenditures accounted for 28.3% of this total amount (Canadian Institute for Health Information, 2018). Operating rooms (ORs) are the largest cost and revenue facility in hospitals (Cardoen, Demeulemeester and Beliën, 2010). ORs are typically the bottlenecks of the appointment scheduling system because they are the most time- and resource-consuming units in hospitals. This can lead to long waiting times for patients and increased OR idle time and overtime. Furthermore, demand for surgical procedures is expected to increase due to higher life expectancy which presents huge challenges for hospitals (Etzioni, 2003). All these factors indicate that improvement in OR efficiency regarding resource utilization, patient flow and on-time treatment are critical for hospitals and society.

Well-designed appointment systems can effectively utilize available providers' time (Gupta and Denton, 2008) and reduce waiting time for patients (Cayirli and Veral, 2003). Inefficient schedules are highly related to OR inefficiency (Weinbroum, Ekstein and Ezri, 2003). Surgery delays and cancellations will be the consequences if ORs cannot be scheduled properly, which results in costs that can be avoided (Buchanan and Wilson, 1996). The main goals for OR managers are to optimize usage of expensive surgeons and OR resources, minimize patients' waiting time and manage surgery variabilities such as procedure duration and complications, late cancellations, delays and emergency arrivals without significantly increasing costs.

Operating room scheduling focuses on the sequence of surgeries for patients as well as resources assigned to each surgery within each OR in a hospital over a day or a week (Jebali et al., 2006). Productivity of surgeons, resource utilization and costs all have an impact on OR scheduling.

The typical OR scheduling problem involves determining the surgery start times or patient appointment time to minimize the expected total cost of OR overtime, idle time, and patient waiting time.

Variability in surgery procedures makes the OR scheduling problem more complicated. First, many different types of procedures are involved in performing surgeries including patient setup and anesthesia, operating room cleaning and setup, surgery execution, and post anesthesia care. Times required for these procedures are variable. Second, procedures themselves are variable. Durations of the same procedure can vary due to patient gender and age (Phan et al., 2018; Puffer et al., 2016), severity of patients' conditions (Kayis et al., 2012), and surgeon tiredness (Wang et al., 2015). Third, unexpected procedure complications can result in longer surgery durations than expected (Persson& Persson, 2010). Fourth, variability of one procedure can have an impact on the whole sequence of activities. For example, poor patient setup will usually lead to poor procedure results and unnecessary complications (Isgett-Lynn, 2011), where the delay will apply to the next surgery scheduled in the same OR.

There are several other factors which complicate the scheduling process. Surgery demands can usually be divided into two categories: elective surgery and emergency surgery. Elective cases are defined as planned ahead, while emergency cases are defined as arriving randomly and having to be performed on the day of arrival (Lamiri et al., 2008). Effective surgery scheduling should have the capability to accommodate emergency cases without significantly increasing elective patient waiting time and OR overtime costs.

Factors such as no-shows, cancellations and delays may also need to be considered. No-shows indicate that patients fail to meet the surgery appointment without informing hospitals in advance. Cancellations mean that surgery arrangements are called off due to either patients or hospitals unable to arrive for the appointment. Delays refer to the length of lateness between actual surgery starting time and scheduled starting time. Any of above will have a negative impact on OR performance including an increase in OR and surgeon idle time and a decrease in OR and resource utilization.

In order to account for the significant variability and complexity in the OR scheduling problem, some recent studies have focused on separating surgery stages and scheduling each stage individually to improve OR efficiency. The administration of anesthesia is an important surgery stage for numerous types of surgeries. It is usually performed within the OR before other procedures start. Non-operating room anesthesia (NORA) is a practice whereby the administration of the anesthesia stage is performed outside the OR. It requires specific training, equipment, and expertise due to challenges associated with the remote location such as inadequate workspaces and lack of support staff, and safe transport of the patient to the OR (Wong et al., 2020). Hospitals can potentially benefit from NORA by scheduling more surgeries since some OR time for each surgery can be saved. However, the scheduling problem becomes more difficult to solve. In this thesis, I investigate scheduling preoperative anesthesia as a separate stage of the surgery process, which will be executed outside the OR by anesthetists. This approach has the potential to save valuable OR and surgeon time.

Different approaches have been developed to solve the OR scheduling problem in prior studies. The most common approaches are optimization and simulation methods. Optimization methods are analytical approaches to achieve optimal schedules. General optimization methods include linear programming, integer programming, mixed integer programming and goal programming. Denton and Gupta (2003) created a stochastic linear programming model to minimize OR overtime and idling costs. Marques et al. (2012) used integer programming to maximize OR utilization. Adan and Visser (2002) proposed a mixed integer programming model to decide patient admission categories. Ozkarahan (2000) adopted goal programming approach to minimize OR overtime and undertime. Simulation methods are usually used to address complexity of large systems and uncertainty. Everett (2002) constructed a discrete-event simulation model to manage elective patients waiting system with emergency arrivals. Paoletti and Marty (2007) used a monte-carlo simulation model to develop schedules with uncertain surgery durations.

Simulation optimization is an approach that combines optimization and simulation. It uses simulation to estimate the stochastic parameters in an optimization model and then solves the problem an using optimization approach. This approach has received limited attention in the surgery scheduling literature. Cayirli and Gunes (2013) used simulation optimization to estimate daily random walk-in numbers and create OR schedules by minimizing total system costs. This approach is useful for the NORA scheduling problem because anesthesia and surgery durations are uncertain and the objective of this problem is to create competitive optimization strategy by minimizing total OR costs.

In this thesis, a simulation optimization approach will be used to find the best solutions for an OR scheduling problem. The goal is to develop schedules for a set of ORs where NORA is used as a practice. The impact of NORA on OR performance will be studied. Since OR efficiency is crucial, its improvement will benefit hospitals both financially and operationally. A simulation optimization model will be developed to determine the best schedules given a NORA policy for a set of outpatient elective procedures. Historical surgery duration data from the Canadian Institute for Health Information (CIHI) on elective outpatient procedures will be used to estimate the input parameters of the model. The data will be fit to probability distributions for surgery durations and anesthesia durations based on intervention codes. The goal is to minimize the expected total cost of surgeon idle time, OR overtime and patient waiting time by implementing NORA policies. Simulation models will then be developed to see how NORA policy can improve OR performance under different operating conditions.

1.2 Research Context

The simplest OR scheduling model is the single-OR model. To illustrate, a basic surgery scheduling system is shown in Figure 1 (adapted from Erdogan and Denton, 2011). OR managers determine the surgery start time for each case and predict surgery durations. If the surgery duration is shorter than predicted, ORs and surgeons' idle time will increase; if the surgery duration is longer than predicted, patient waiting time may increase and the whole sequence of OR activities may be affected. This can result in surgeon and OR overtime. Scheduling problems are complicated since managers need to decide the procedures to be performed, resources to be allocated to those procedures and sequencing of procedures (May et al., 2011). These all contribute to the complexity of surgery duration prediction, which will ultimately affect OR efficiency.

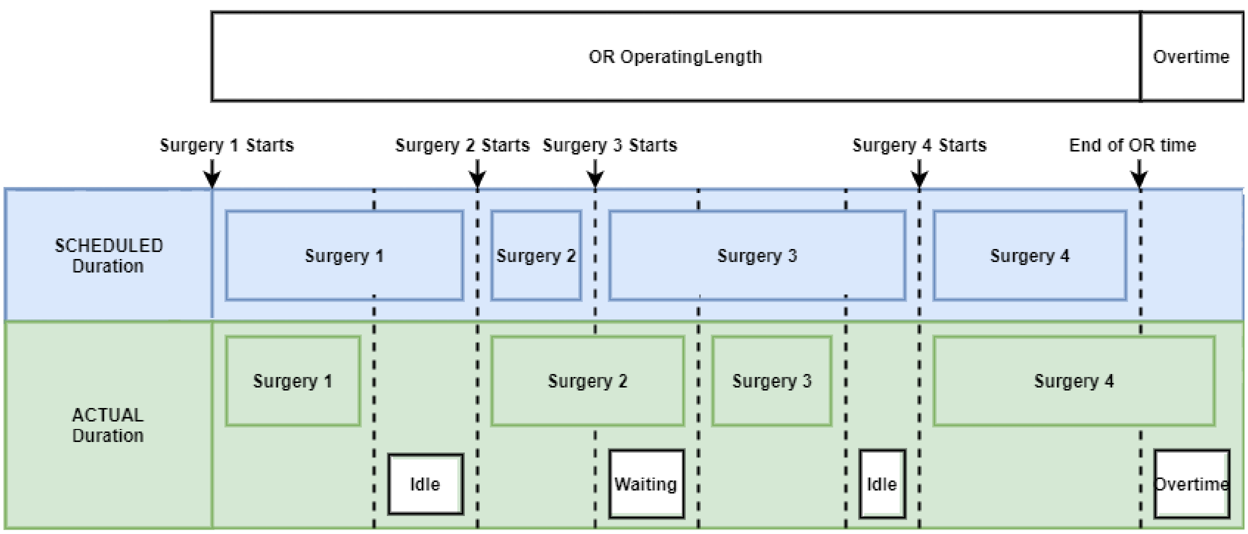

Figure 1. Basic Surgery Scheduling for Single OR

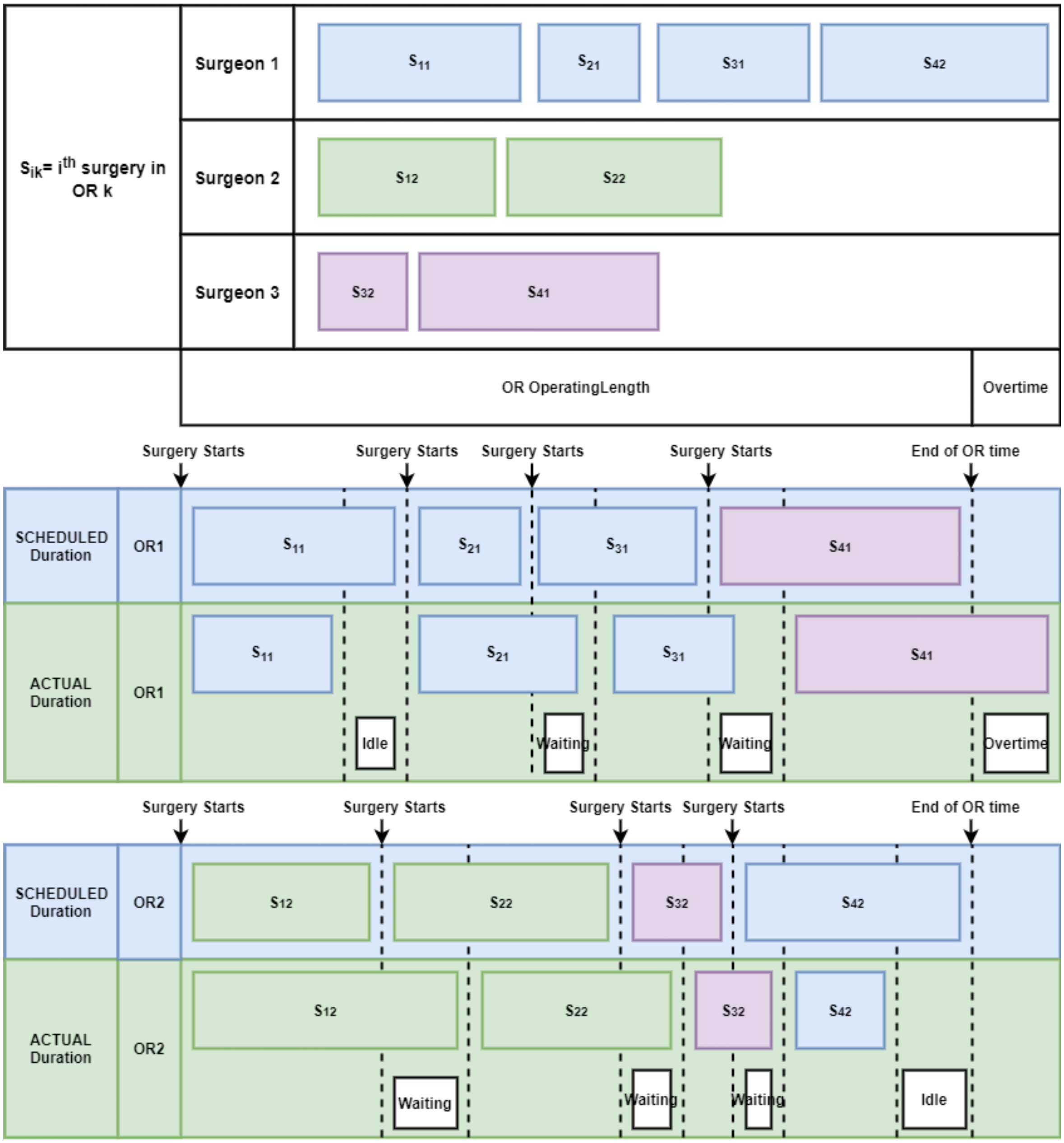

Figure 2. Feasible Schedule for multiple surgeons sharing multiple ORs

OR scheduling problems become more challenging when multiple ORs are involved. Scheduling in multiple ORs also requires a manager to determine the surgery start time for each case and predict surgery durations. Figure 2 shows an example of a feasible schedule for three surgeons sharing two ORs where S_{ik} represents the i^{th} surgery in OR k. For example, Surgeon 1 will perform the first, second and third surgery scheduled in OR1 and the fourth surgery in OR2;

Surgeon 2 will perform first and second surgery in OR2. All surgeries are planned to be finished within the OR operating session (e.g., eight hours per day) and surgeons may perform surgeries across ORs. Surgery duration uncertainty may affect efficiency of the whole system because under resource sharing conditions, one delay in one OR may cause a delay in the other OR. For example, Surgeon 3 is scheduled to perform the first surgery in OR 2 and the second surgery in OR 1, while delay of the first surgery leads to the delay of the second surgery.

More recently, studies have focused on analyzing each of the surgery stages separately to determine if some of the activities can be scheduled in parallel or if some of the required resources can be pooled to improve OR efficiency. Figure 3 shows the typical stages of the surgery process for a patient. Elective patients need to go through three stages in hospitals: pre-operation, operation and post-operation. Stage 1 (pre-operation) usually takes place in preparation areas, where patients get ready for surgery. Stage 2 (operation) happens in the OR where patients go through the whole surgery. Stage 3 (post-operation) is the recovery stage where patients recover from the surgery. More specifically, Stage 2 in ORs consists of a sequence of activities, which can also be divided into three stages: Stage 2-1 pre-incision, Stage 2-2 incision and Stage 2-3 post-incision (Batun et al., 2011). Stage 2-1 includes positioning patient in OR and anesthesia, while Stage 2-3 includes cleaning the OR. In this study, the focus is on scheduling elective surgeries in ORs and pooling resources for non-clinical portions of the procedures (Stages 2-1 and 2-2). Non-operating room anesthesia (NORA), which occurs at Stage 2-1, is investigated since it meets both requirements of being implemented outside the OR and being a non-clinical portion activity. NORA is an alternative way of implementing pre-incision stage processes. It will create another stage that will be performed outside the OR before the surgery starts and thus, reduce OR time required for each surgery.

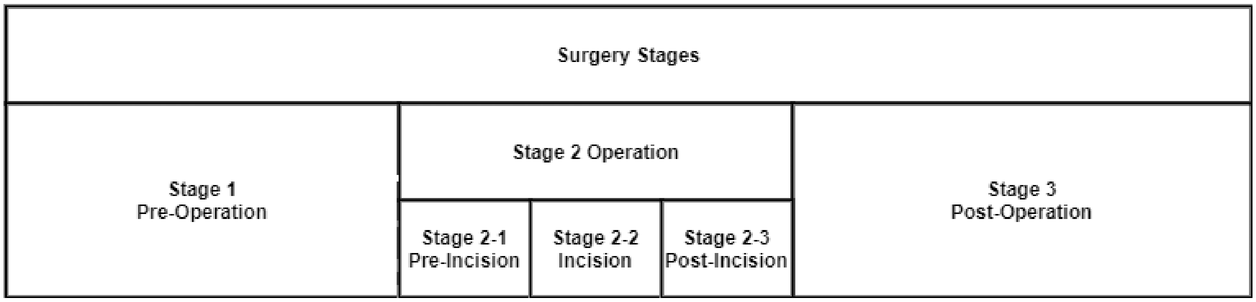

Figure 3. Surgery Procedure Stages and NORA procedure

NORA case volumes keep increasing year by year (Nagrebetsky et al., 2017) and NORA-based procedures comprise a larger share of modern anesthesia practice than ever before (Chang et al., 2018). Concerns regarding safety issues in NORA have been raised, but NORA is claimed to have lower morbidity and mortality rates than OR procedures (Chang et al., 2018) and overall is considered safe for patients (Woodward, Urman, and Domino, 2017). NORA requires a thorough pre-anesthetic assessment for patients and NORA sites need to be strictly monitored for patients. Procedures that require highly specialized personnel or need to be performed on patients with complicated conditions are not suitable for NORA sites.

Figure 4 shows a sample feasible schedule for three surgeons and two ORs with a NORA policy. Each surgery consists of an initial anesthesia stage (a) and the remaining procedures (e.g., incision, post incision) in Stage 2. S_{ik}^{a} represents anesthesia procedure for *i*th surgery in OR *k* where S_{ik}^{r} represents the remaining procedures for *i*th surgery in OR *k*. For example, Surgery 1 of Surgeon 1 has initial anesthesia procedure time of S_{11}^{a} and the remaining procedure time is S_{11}^{r} in the blue block. The initial anesthesia procedure will be performed outside the OR in a separate NORA area. The patient is then moved to the OR to perform the remaining stages of the surgery. Compared to Figure 2, all the surgeries performed in the ORs are shorter since the anesthesia component has been subtracted from OR procedure times. As shown, the benefit from this approach is that time in the OR is saved and those time blocks can be released for other purposes.

NORA policies allow ORs to save time compared with traditional OR scheduling. These saved times can be used to schedule more surgeries, which will improve OR throughputs. Since durations of surgeries in the OR are shorter, NORA policies also give hospital managers more flexibility to manage surgeries that take longer than expected without significantly affecting waiting times of other patients.

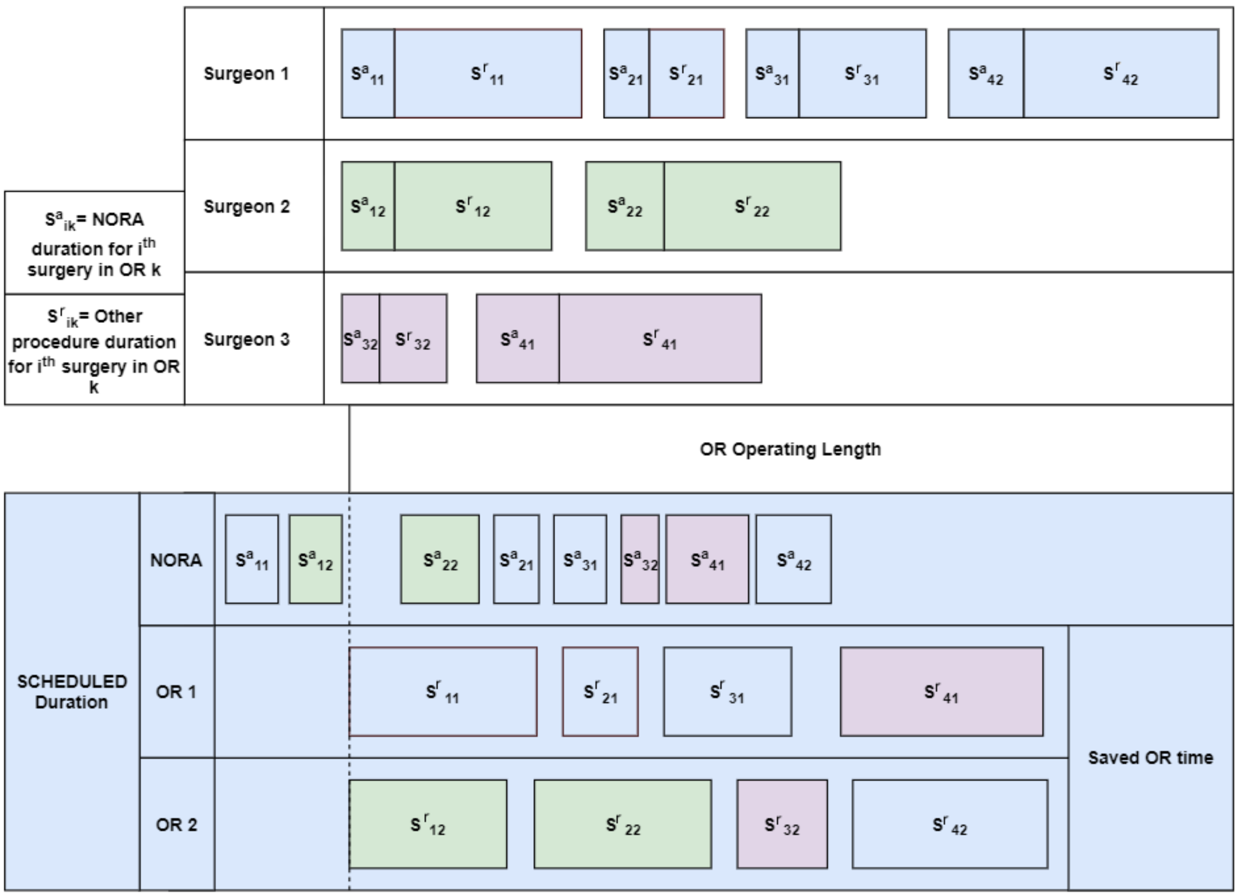

Figure 4. Feasible Schedule for applying NORA policies to OR scheduling

1.3 Research Goals and Contribution

Prior literature has extensively studied surgery scheduling using analytical methods. They were used to develop optimal surgery schedules and optimize performance measures. Optimization using mathematical programming and simulation are the most common methods found in the literature. Optimization approaches offer optimal results and can mostly be solved in a short amount of time, but they lack the ability to address complicating factors such as surgery duration uncertainty, emergency arrivals, no-shows and cancellations. Simulation approaches can deal with uncertain factors and can simulate situations close to reality, but they are time-consuming to produce results and the optimization results are usually not competitive. The advantages for combining these two approaches are (1) computation times can be saved, which means scheduling decisions can be quickly adjusted due to uncertainty, (2) complicating factors can be addressed, which offers general insights for practical use and (3) different scenarios can be tested without changing the real system. Thus, simulation optimization is an effective approach to use in this study.

The main objective of this research is to develop surgery schedules that minimize the expected total cost of patient waiting time, surgeon idle time, and OR overtime by implementing NORA policies using a simulation optimization approach. NORA has the potential to improve OR efficiency by increasing utilization of OR resources and making OR scheduling more flexible. NORA and surgery durations are both uncertain, which makes the simulation optimization approach suitable for the problem because it can resolve complex multi-stage problems with uncertainty. This research will also investigate the impact of variability in surgery duration and duration of different procedure types on developing surgery schedules in an outpatient setting. Different surgeries have their own traits and NORA policies may offer more flexibility with some duration uncertainty. Differences in the mean and standard deviation of surgery durations can all have impacts on NORA policy applications. Scenario analysis will be used to study the impact of these factors.

In this thesis, a simulation optimization model will be developed to determine the sequence of surgeries in each OR and the start time for NORA and each surgery. Results of a scheduling policy with NORA and a traditional scheduling policy will be compared in terms of OR efficiency and expected total cost. Different means and standard deviations used for distributions of surgery durations will also be examined for to determine the impact of implementing NORA on OR performance.

To validate the performance of different policies, historical surgery duration data from the Canadian Institute for Health Information (CIHI) will be used to develop probability distributions for anesthesia operating time and surgery operating time broken down by intervention types and codes. They will be used as input for the simulation optimization model. The simulation optimization algorithm will be embedded in OptQuest (OptTek Systems, Inc. 2005) with the simulation model developed in ARENA 14.0 (Rockwell Software, Inc. 2005)

This research contributes to the literatures in several ways. First, NORA has been studied on its financial and operational gains in some studies but has rarely been studied on improving OR scheduling and efficiency. This study is expected to provide insights on how NORA policies can maximize OR utilization without significantly increasing patient waiting time, idle time and overtime. Second, different surgery types can have diverse mean durations and standard deviations. This study will investigate how NORA policy will perform when these conditions change. Third, this study will hopefully provide insights on efficient ways to incorporate NORA for practical use under various environments.

This thesis is organized as follows. Chapter 2 discusses the literature in surgery scheduling. Chapter 3 presents the formulation of the traditional and NORA scheduling problem. Chapter 4 provides results from traditional and NORA models and scenario analysis. Chapter 5 summarizes the conclusions for this research.

2 Literature Review

Appointment scheduling problems in ORs have been extensively studied in the literature. Scheduling policies (e.g., open and block scheduling), analysis methodologies (e.g., goal programming and monte-carlo simulation) and resource constraints (e.g., number of ORs, number of surgeons) have all been used in numerous papers. Recent research tends to break down surgeries into stages to see whether some of the stages can be performed by either pooling the resource or scheduling surgeries in parallel. This thesis focuses on studying multi-stage OR block scheduling problems considering non-OR resource pooling. NORA procedures are performed outside the OR and require resources including anesthetists, anesthesia equipment and nurses. These anesthesia-related resources are pooled in NORA area. The literature relating to scheduling system, performance measures, methodologies and resource pooling will be covered in this chapter.

2.1 Scheduling Policies

There are primarily three scheduling systems that exist in the literatures. They are open scheduling system, block scheduling system and modified block scheduling system. In this section, the literature on designing schedules under these three systems will be reviewed. They will be compared to see which one will be useful to solve the problem in this thesis.

2.1.1 Open Scheduling

Open scheduling refers to assigning surgeries to available ORs when surgeons can choose any workday for a case. Surgeons can submit their surgical cases until the day of surgery. Open scheduling was also simplified as a “First Come First Serve (FCFS)” policy (Patterson, 1996), which accommodated patients based on registering orders. It is usually used for patients to book appointments with their personal physician.

Guinet and Chaabane (2003) used an open scheduling policy and focused on assigning patients to ORs. They built an integer programming model to minimize OR overtime and patient waiting costs. They solved the problem by applying a primal-dual heuristic where the dual solutions were developed by relaxing constraints based on primal solutions. They found most of problems in their experiments could be entirely solved within reasonable computation times. Jebali, Alouane and Ladet (2006) adopted open scheduling policies to assign and sequence surgical cases using a two-step mixed integer programming. One of the constraints was that assigning an operation to an OR where the required equipment was not allowed. The first step was assigning operations to ORs, where hospital daily costs, OR undertime and overtime costs were minimized. The second step was sequencing operations that were assigned at the previous step, which targeted at minimizing OR overtime. Sequencing strategies of pure sequencing and sequencing with re-assignment were compared by numbers of optimal solutions generated in limited computational times. Fei, Chu and Meskens (2009) adopted open scheduling strategy and first formulated an integer programming model to minimize total OR undertime and overtime costs. They then reformulated the problem as a set-partitioning model so they could solve the problem by proposing column-generation-based heuristic procedures. They managed to create efficient schedules with reasonable computation time when non-OR resources were well organized.

2.1.2 Block Scheduling

Block scheduling refers to assigning time blocks to specific surgeons and assigning surgeries to time blocks. Blocks are reserved for the surgeons and cannot be released in theory. Surgeons will try to fit all surgical procedures within time blocks. Block scheduling problems are usually solved in two steps (Fei et al., 2009).

The first step is to develop a Master Surgical Schedule (MSS), which is defined as a cyclic timetable that determines the surgical unit associated with each block of OR time (Testi et al., 2007). Blake, Dexter and Donald (2002) used integer programming to assign blocks to surgical groups operating at a surgical suite. The MSS produced from their model was not time-consuming thus they could be applied to numerous circumstances. Beliën, Demeulemeester and Cardoen (2008) developed MSS for assigning surgical units to OR blocks. The three objectives of MSS are to optimize the bed occupancy, limit OR sharing among different surgeon groups and develop repetitive MSS. They adopted hierarchical goal programming models to solve the problem by optimizing one objective after previous objective was optimized. Simulated annealing was the other heuristic they used to solve the problem by trying random variations of current solution. They compared their results with different algorithm runs and provided managers with limits of different MSSs. Adan et al. (2008) proposed an integer programming model with stochastic length of stay variables to determine surgical units that should be assigned to OR blocks. Their objective was to maximize OR utilization under staffs and wards limitation. Their results showed that it was very important to consider stochastic durations in generating optimal MSS.

The second step is referred as Elective Case Scheduling (ECS), which schedules elective cases in allocated blocks and determines the sequence of surgical cases. Fei et al. (2008) formulated an integer programming problem aiming at assigning patients to OR blocks with minimal costs. They then reformulated the model into set partitioning master problem and developed branch-and-price solution algorithm to optimally solve the problem. They tested their model with randomly generated data and found computations times were reasonable after applying the heuristic. Cardoen, Demeulemeester and Beliën (2009) established a multi-objective function model which optimized surgery scheduling of children, prioritized patients, travel distance between patient's residence and the day-care center, overtime hospitalization and peak number of bed spaces in PACU simultaneously. They used basic and modified mixed integer programming approaches to find optimal surgeries sequence. Modified approaches were compared with basic approach for their computation times and gaps. Marques, Captivo and Vaz Pato (2012) used integer programming to plan an optimal weekly schedule for elective patient assignment aiming at reducing wait list and performing more surgeries. Optimal solutions could be found in different specialty cases, but computation times and cancellation rates were high. Improved heuristics were developed by exchanging unscheduled surgeries with surgeries which would run overtime, which saved computation time and reduced cancellation rates.

2.1.3 Modified Block Scheduling

Modified block scheduling is an advanced block scheduling system. It leaves some time blocks open or release unused time blocks before surgery. Dexter (2000) adopted modified block scheduling strategy to reduce overtime labor costs by developing better surgical case allocation. He used an approach to determine the time of transferring the last case of the day to another available OR in terms of minimizing overtime staff costs. Fei, Meskens and Chu (2010) formulated a two-stage approach to determine daily schedule of ORs and recovery room using modified block scheduling system.

Open scheduling policy has more flexibility and tends to find better surgery assignment than block scheduling, but they are rarely adopted (Guerriero and Guido, 2011). The complexity of open scheduling systems especially of surgeries sequencing makes it difficult to find optimal solutions, while many researches solve problems by either adopting heuristics or building multi-step models. Block scheduling policy assigns surgeons and patients to OR blocks, which is an easier approach than open scheduling since blocks are pre-determined. It also makes it less flexible since blocks cannot be released. The flexibility and complexity of modified block scheduling policy are in between two policies mentioned above.

This thesis will involve OR and NORA rooms and elective and emergent patient allocation. Both open scheduling policy and modified block scheduling policy are difficult to solve in multi-stage problems due to sequencing complexity. Thus, in this thesis, the application of NORA policy will be investigated in a block scheduling environment.

2.2 Performance Measures

Various performance measures are used to evaluate OR scheduling in block scheduling problems. The most common ones found in the literature are OR overtime and idle time, patient waiting time and OR costs. Some studies are concerned about reducing patient waiting time without significantly increasing costs. Cardoen and Demeulemeester (2008) proposed a discrete-event simulation approach to simultaneously evaluate multiple surgical activities sequences. They incorporated surgery duration and patient arrival uncertainty into the model. Patient waiting time and surgeon overtime were the performance measures they used to evaluate sequencing rules in simulation model. Lovejoy and Li (2002) investigated trade-offs among indirect patient waiting time, surgery start-time reliability and hospital profits. A series of integer programing models were proposed to study these trade-offs. They used their findings to generate suggestions for hospitals on how to expend OR capacity. VanBerkel and Blake (2007) built a simulation model for flow of elective and non-elective patients through the OR and into the recovery area. Patient waiting time and OR throughput were the measures to be compared. They claimed that effective uses of current resources were fundamental to reduce waiting time.

OR cost is one of the most common performance measures. Since OR overtime and undertime will both contribute to high OR costs, many studies aim to minimize both criteria to reduce OR costs. Denton, Viapiano and Vogl (2007) formulated a two-stage stochastic mixed integer programming model to develop OR schedules aiming at minimizing patient waiting time and OR idling time. Numerical experiments based on real surgery scheduling data were carried out for analysis. They found that improvements to optimal OR schedules were sensitive to sequencing decisions and effects of optimal sequencing depended on relative importance of performance measures. Dexter and Macario (2004) used scenario analysis to detect the impact of postponing decisions on releasing unscheduled surgical blocks for new cases on OR overtime. Releasing allocated OR time the day before the surgery could reduce OR overtime compared with releasing allocated OR time 3 to 5 days before the surgery. Results were claimed to be true for both medium-sized and large surgical suites. Vissers, Adan and Bekkers (2005) developed mixed integer programming to minimize OR overtime and undertime. ORs, staffs and recovery resources were all considered at the same time. Different environment settings such as adding extra resources, using weekend scheduling policy and receiving bypass operations were tested to be compared with ideal performance schedules for OR utilization. Ma et al. (2009) solved a session planning (SP) problem using integer programming and branch-and-price algorithms. They aimed at maximizing hospital profits under limited admissions and capacity of surgeons. They found that branch-and-price algorithms outperform integer programming approach on both solution quality and computational speed.

This study will focus on minimizing costs relating to OR overtime and undertime since this thesis wants to detect the impact of NORA policies on OR efficiency. Patient waiting time is also important but it is not weighted as heavily given that surgeon and OR resources are significantly more expensive. Improving OR utilization and throughput will also have a positive impact on decreasing patient waiting time.

2.3 Methodologies

A wide range of research methodologies exist in the current literature on OR scheduling. Many optimization methods were adopted since they could provide optimal results. They can aim at optimizing single or multiple objectives under resource constraints. Parameters in optimization model are usually certain.

Goal programming is an optimization method that deals with multi-objective problems. Ozkarahan (2000) adopted goal programming approach to minimize OR overtime and undertime. The model also considered block restriction, surgeon preference and ICU capability. Models were tested based on data from performed operations and requested surgeries. The results showed that a goal programming approach was suitable for achieving multiple objectives including minimizing OR overtime and undertime, and increasing satisfaction of staffs and patients. Blake and Carter (2002) developed two linear goal-programming models to preserve physician income and minimize hospital costs. Their models could be used to decide resource allocation by considering OR capacity and physician preferences. Ogulata and Erol (2003) constructed multiple criteria mathematical programming models that aimed at maximizing OR utilization, balancing the allocation of surgeons to ORs, and reducing patient waiting time. They broke down the problem into hierarchical stages namely patient selection, surgeon assignment and OR allocation. A goal programming approach based on three stages were adopted to ease computational difficulties.

Discrete-event and monte-carlo simulation have also been used in by many studies. The advantage of simulation is that it can easily address uncertainty. Everett (2002) constructed a discrete-event simulation model to manage elective patients waiting system. Patients were categorized by urgency and type of operation. The model was used to dynamically maintain waiting list based on actual operating hours. Dexter and Traub (2002) adopted discrete-event simulation model to maximize OR utilization. Scheduling rules of earliest start time and latest start time were investigated through different scenarios. Earliest start time had a better performance economically while latest start time had a better performance in balancing workload. Paoletti and Marty (2007) used monte-carlo simulation to examine the risk of no available anesthetists when required. The durations of surgery inductions were generated from real values of a hospital. Different scenarios of scheduling, staffing ratio and number of ORs were studied.

Several papers adopted both optimization and simulation methods for scheduling. Lamiri et al. (2007) proposed an optimization model to minimize patients related costs and OR planning costs. Monte-carlo simulation was used to incorporate uncertainty of surgery time and emergency arrivals. Problem was solved by applying column generation approach to get near optimal solutions. Testi et al. (2007) used mixed integer programming to develop SP schedule and MSS. Optimal weekly session numbers and OR assignments were used as constraints in simulation model. Simulation model was carried out considering random surgery duration and patient priority. Their goal was to maximize same number of surgery appointments and minimize overrun hours in an integrated way. Persson and Persson (2010) first used simulation model to determine patient arrivals. An optimization model was then developed to determine surgery schedules for following

4 weeks. Each day the schedule would update due to uncertainty including new emergency arrivals, cancellations and over-time restrictions. Their goal was to minimize costs relating to OR planning and maximize medical responsiveness.

Simulation optimization is an approach which solves stochastic optimization programming model by simulating stochastic parameters. Klassen and Yoogalingam (2009) adopted simulation optimization approach to determine optimal rules for stochastic scheduling problem. They used simulation model to estimate the mean length of surgery sessions and formulated optimization model to minimize total cost if waiting, idle and overtime. Cayirli and Gunes (2013) used simulation optimization to estimate daily random walk-in numbers and studied seasonal impacts of walk-ins by minimizing total system costs combining patient waiting time, physician idle and overtime. The advantages of simulation optimization method are that (1) it can accommodate stochastic parameters, and (2) it can simultaneously study multiple cases, which saves time.

Simulation optimization approach will be used in this thesis since it has the capability of accommodating both uncertain durations and complex multi-objective problems. This method can achieve competitive results in reasonable computation time compared to simulation approach.

2.4 Resource Pooling

More recently, researchers have interests in separating surgery stages to pool the resources to improve OR efficiency. Saremi et al. (2013) divided surgeries into pre-operation, operation and post-operation stages. Different stages would have different resource limitations and process times. They developed new approaches based on tabu search to optimally solve the problem and compared performances of several scheduling rules. Batun et al. (2011) used mixed integer programming to minimize operating costs with uncertainty of surgery durations. They quantified the benefit of pooling ORs and illustrated the impact of parallel surgery processing. They found the impacts of both processes were significant.

NORA was statistically studied for its trend and performance. Nagrebetsky et al. (2017) claimed that proportion of NORA cases improved from 28.3% in 2010 to 35.9% in 2014. NORA performed more often after working hours than normal OR anesthesia. Outpatient NORA cases increased from 69.7% in 2010 to 73.3% in 2014. Thus, NORA appears promising in terms of improving OR efficiency in terms of the number of surgeries that can be scheduled.

In this study, NORA policies will be investigated for its performance on block scheduling systems where NORA procedures will be executed outside ORs. There have been few studies that have examined the impact of NORA practices on surgery scheduling in a multi-OR setting. In this thesis, the main focus is to see how NORA affects OR efficiency and how it can improve OR performance using a simulation optimization approach.

3 Problem Formulation

The research proposes a simulation optimization approach for a NORA scheduling problem. The NORA policy will be discussed on what it represents and its role in a surgery. A single-OR simulation optimization model will be formulated to represent a basic situation which produces results without NORA for comparison. The model will be extended to include a NORA policy to determine the impact of NORA in a single-OR setting. A multiple-OR model will also be formulated to capture the NORA problem in a more complicated setting.

3.1 Stages of the Anesthesia Process

Typically, general anesthesia has four stages. Stage I is Induction and begins with the first administration of anesthesia. Stage II is the Excitement stage which follows the loss of consciousness. Stage III is Surgical Anesthesia where the patient is in the state in which the surgeon can perform the procedure. The anesthesiologist's primary job in surgery is to expedite the patient's progression to this stage and to keep him or her stable in it until the surgeon is finished. The anesthesiologist must avoid progression into Stage IV, or Overdose. In this stage, the patient has received an excess of medication. If the medical team does not bring the patient out of Stage IV quickly, the experience can be fatal. Stage I and II occur during the Stage 2-1 in Figure 3 and Stage III occurs during the Stage 2-2.

Costa (2017) offered another view of the processes taking place in the OR. He divided the process into 5 stages: (1) time between the patient’s entrance in the room and beginning of anesthesia (anesthetic induction); (2) time between anesthetic induction and beginning of procedure; (3) duration of procedure; (4) time between the end of the procedure and the end of anesthesia (awakening); (5) time between ending of anesthesia and patient exit from the room.

Based on Figure 3, Stage (1) and (2) occur at the Stage 2-1, Stage (3) occurs at the Stage 2-2, and Stage (4) and (5) at the Stage 2-3. An illustration of the anesthesia stages is shown in Figure 5.

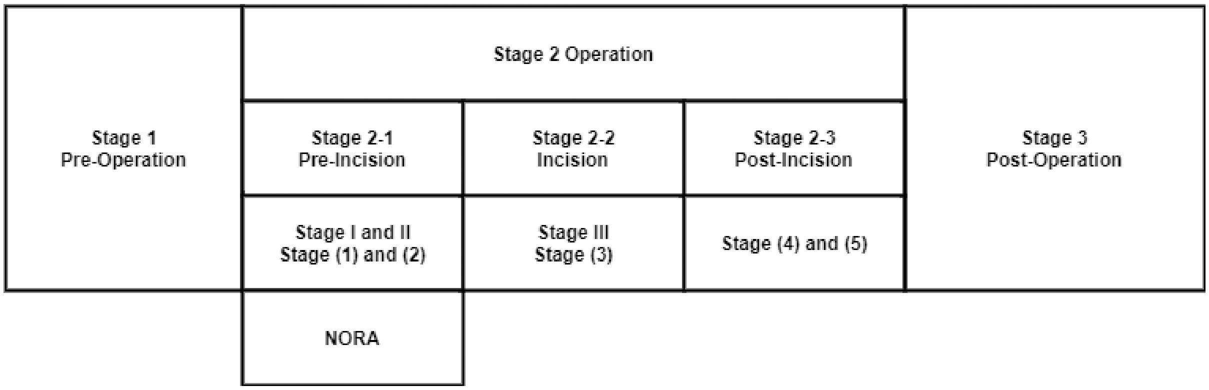

Figure 5. Comparing anesthesia stages with Typical surgery procedures

As shown in Figure 5, Stages (1) and (2), or Stage 2-1 in Figure 3, is the portion of the anesthesia process that can safely take place outside of the OR. In this thesis, this stage will be modeled as a separate component of the surgery process.

3.2 Problem Formulation

The objective of this scheduling problem is to optimize OR efficiency by reducing OR overtime, idle time and patient waiting time where anesthesia at the pre-incision phase of the surgery process is performed outside the OR. Expected total costs related to patient waiting time, OR idle time and over time will be the performance measure. Three models are developed. First, a single-OR simulation optimization model for surgery scheduling without NORA is formulated as Model 1. Second, a single-OR model with a NORA policy will be formulated as Model 2. Third, Model 2 is extended to include multiple ORs and surgeons as Model 3. The results of the Model 1 will be compared with a NORA model to determine how NORA policy can improve OR efficiency.

3.2.1 Basic Model: Single-OR with no NORA

Model 1 is a basic OR scheduling problem that assigns surgeries to a single-OR. The objective is to minimize the weighted sum of the expected total cost of patient waiting time, OR idle time and overtime. In this problem, it is assumed that the patients have similar service time characteristics.

The notation used in the model is as follows:

N: Number of patients to be scheduled

d: Session length in minutes

c_{wt}: Cost coefficient for patient waiting time (The time between patient arrival and surgery start time)

c_{ot}: Cost coefficient for overtime (The time beyond scheduled OR session length)

c_{it}: Cost coefficient for idle time (The time that OR is in use)

The decision variable is:

x_i: Appointment start time for patient $i \ for \ \forall i \in (1,2,\dots,N)$

The actual surgery duration for each patient in the simulation model is shown as follows and is a random variable drawn from a distribution:

s_i: Surgery duration of patient i for $\forall i \in (1,2,\dots,N)$

The following notation is used for the performance measures:

WT_i: Waiting time of patient i

IT_i: Idle time between patient i and $i-1$

OT: Length of overtime

Since we assume that the first appointment starts at the beginning of the session ($x_1 = 0$), we have $WT_1 = 0$ and $IT_1 = 0$. The performance measures for $i = 2, \dots N$ are defined as follows.

$$WT_i = Max\{x_{i-1} + WT_{i-1} + s_{i-1} - x_i, 0\} \tag{1}$$

$$IT_i = Max\{x_i - [x_{i-1} + WT_{i-1} + s_{i-1}],0\} \quad (2)$$

$$OT = Max\{x_N + WT_N + s_N - d, 0\} \quad (3)$$

Given cost coefficients for patient waiting time (c_{wt}), OR idle time (c_{it}) and overtime (c_{ot}), the model is formulated as a weighted sum of the three performance measures.

$$Min\ c_{wt}E\left[\sum_{i=1}^{N} WT_i\right] + c_{it}E\left[\sum_{i=1}^{N} IT_i\right] + c_{ot}E[OT] \quad (4)$$

$$s.t.\ 0 \leq x_i \leq d\ \forall i \quad (5)$$

$$x_1 \leq x_2 \leq \cdots \leq x_N \quad (6)$$

$$x_i \text{ integer} \quad (7)$$

3.2.2 NORA Model: Single-OR Model with NORA

The model presented in this section extends the single-OR model to one with a NORA policy. It puts Stage 2-1 (Pre-Incision) outside OR for the single-OR setting. The goal is to formulate a model that can accommodate NORA policy and see how it can improve single-OR efficiency.

The notation used in the model is as follows:

N: Number of patients to be scheduled

d: Session length in minutes

c_{wt}: Cost coefficient for patient waiting time

c_{ot}: Cost coefficient for overtime

c_{it}: Cost coefficient for idle time

The decision variables are:

x_i: Appointment start time (Anesthesia Start Time) for patient i for $\forall i \in (1,2, \ldots, N)$

y_i: Surgery start time in the OR for patient i for $\forall i \in (1,2, \ldots, N)$

The actual surgery durations for each patient in simulation model are random variables drawn from a distribution and are represented as follows:

s_i^a: NORA duration of patient i for $\forall i \in (1,2,\ldots,N)$

s_i^r: Surgery duration of patient i for $\forall i \in (1,2,\ldots,N)$

Compared to model in Section 3.2.1, the appointment is split into the NORA procedure (Stage 2-1), which is performed outside the OR, and other surgery procedures (Stage 2-2 and 2-3), which are performed inside the OR. We assume that the sum of NORA and other procedure durations is equal to the whole appointment duration in Section 3.2.1.

$$s_i^a + s_i^r = s_i$$

The following notation is used for the performance measures:

WT_i^x: Waiting time of patient i

IT_i^y: Idle time between patient i and $i-1$

OT: Length of overtime

Three assumptions are thus made: (1) Patients will go through a NORA procedure when the previous surgery ends and turnover time (i.e., clean OR, prepare OR for next surgery) starts in the OR if their waiting time is positive; (2) Transition time from the NORA area to the OR will be ignored; (3) the NORA duration is always longer than the turnover time. Since we assume that the first appointment starts at the beginning of the session ($x_1 = 0$), we have $WT_1^x = 0$ and $IT_1^y = 0$. The performance measures for i = 2, ... N for a single-OR with a NORA policy are defined as follows:

$$WT_i^x = Max\{x_{i-1} + WT_{i-1}^x + s_{i-1}^a + s_{i-1}^r - x_i, 0\} \quad (8)$$

$$IT_i^y = Max\{y_i - [y_{i-1} + IT_{i-1}^y + s_{i-1}^r], 0\} \quad (9)$$

$$OT = Max\{y_N + s_N^s - d, 0\} \quad (10)$$

NORA allows Stage 2-1 (Pre-Incision) to be performed outside OR, which leads to waiting lines for NORA procedure and OR procedures. Patient waiting time is calculated based on waiting line of NORA procedure, where the decision variable is the appointment time for patients; idle time is calculated based on waiting line of OR procedures, where decision variable is surgery start time for patients and surgeons. The objective is to minimize the expected total cost of patient waiting time, idle time and overtime.

$$Min\ c_{wt}E\left[\sum_{i=1}^{N} WT_i^x\right] + c_{it}E\left[\sum_{i=1}^{N} IT_i^y\right] + c_{ot}E[OT] \tag{11}$$

$$s.t.\ x_i + s_i^a \leq y_i \tag{12}$$

$$0 \leq x_i \leq d \qquad \forall i \tag{13}$$

$$x_1 \leq x_2 \leq \cdots \leq x_N \tag{14}$$

$$y_1 \leq y_2 \leq \cdots \leq y_N \tag{15}$$

$$x_i\,, y_i \text{integer} \tag{16}$$

Constraint (12) ensures that patients cannot start their surgery procedures before finishing the NORA procedure. Constraint (13) ensures that patients have to be scheduled before the end of the day. Constraint (14) and (15) ensure the sequence of appointments.

3.2.3 Extended NORA Model: Multiple OR model with a NORA policy

The formulation in Section 3.2.2 is extended to a multiple OR and surgeon setting because hospitals normally have more than one OR. The multiple OR model allows Stage 2-1 (Pre-Incision) of surgery from all ORs to be performed in same remote location.

The notation used in the model is as follows:

$$K: Number\ of\ ORs, k = 1, 2, \ldots, K$$

$M: Number\ of\ surgeons, m = 1, 2, \ldots, M$

N_k: Number of patients to be scheduled in OR k , $k = 1, \ldots, K$

d: Planned session length in minutes

c_{wt}: Cost coefficient for patient waiting time

c_{ot}: Cost coefficient for over time

c_{it}: Cost coefficient for idle time

The decision variables are:

x_{ik}: Appointment start time (Anesthesia Start Time) for i^{th} patient to OR k $\forall i \in (1,2, \ldots, N_k)$

y_{ik}: Surgery start time for i^{th} patient assigned to surgeon *m* in OR k $\forall i \in (1,2, \ldots, N_k)$

The surgeon assigned to specific surgery is defined as follows:

$$M_{ik}: \begin{cases} 1 & \text{Surgeon } m \text{ is assigned to the } i^{th} \text{ patient to OR } k\ \forall i \in (1,2, \ldots, N_k) \\ 0 & \text{Surgeon } m \text{ is not assigned to the } i^{th} \text{ patient to OR } k\ \forall i \in (1,2, \ldots, N_k) \end{cases}$$

The actual surgery durations for each patient in the simulation model are random variables drawn from a distribution and are represented as follows:

s_{ik}^a:NORA duration of i^{th} patient in NORA area k $\forall i \in (1,2, \ldots, N_k)$

s_{ik}^r: Surgery duration of i^{th} patient in OR k $\forall i \in (1,2, \ldots, N_k)$

Similar to Model 2 in Section 3.1.2, we assume that the sum of NORA and other procedures durations for i^{th} patient in OR *k* is equal to the surgery duration which is solely operated in OR *k*.

$$s_{ik}^a + s_{ik}^r = s_{ik}$$

The following notation is used for the performance measures.

WT_{ik}^x: Waiting time of i^{th} patient in OR k associated with x_{ik}

IT_{ik}^y: Idle time of i^{th} patient in OR k associated with y_{ik}

OT_k: Length of overtime for OR k

Assumptions (1) – (3) in Section 3.2.2 still apply to the model in this section. Additional assumptions are: (4) Resources required for NORA are unlimited, which means NORA procedures of different ORs can be performed simultaneously; (5) Surgery procedures across ORs are similar which do not require specific groups of surgeons for certain procedures.

We assume that the first appointment starts at the beginning of the session ($x_{1k} = 0\ \forall k$). Thus, $WT_{1k}^{x} = 0$ and $IT_{1k}^{y} = 0$. The performance measures for multiple OR model with NORA policy are defined as follows for i = 2, …, N_k and $k = 1$, …, K:

$$WT_{ik}^{x} = Max\{x_{(i-1)k} + WT_{(i-1)k}^{x} + s_{(i-1)k}^{a} + s_{(i-1)k}^{r} - x_{ik}, 0\} \tag{17}$$

$$IT_{ik}^{y} = Max\{y_{ik} - [y_{(i-1)k} + IT_{(i-1)k}^{y} + s_{(i-1)k}^{r}], 0\} \tag{18}$$

$$OT_k = Max\{y_{N_k} + s_{N_k}^{r} - d, 0\} \tag{19}$$

The objective is to minimize the expected total cost of patient waiting time, idle time and overtime.

$$Min\ c_{wt}E\left[\sum_{i=1}^{N}\sum_{k=1}^{K} WT_{ik}^{x}\right] + c_{it}E\left[\sum_{i=1}^{N}\sum_{k=1}^{K} IT_{ik}^{y}\right] + c_{ot}E\left[\sum_{k=1}^{K} OT_k\right] \tag{2}$$

$$s.t.\ x_{ik}^{a} + s_{ik}^{a} \leq y_{ik} \tag{3}$$

$$\sum_{i=1}^{N}\sum_{k=1}^{K} M_{mik} \leq 1 \quad \forall\, m \tag{20}$$

$$0 \leq x_{ik} \leq d \qquad \forall i, k \tag{21}$$

$$x_{1k} \leq x_{2k} \leq \cdots \leq x_{Nk} \tag{22}$$

$$y_{1k} \leq y_{2k} \leq \cdots \leq y_{N_k} \tag{22}$$

$$x_{ik}\,, y_{ik}\text{integer} \tag{23}$$

The roles of constraints in this model are identical to ones described in Section 3.2.2 with an addition of constraint (22), which ensures that there is no surgeon overlap among ORs.

3.3 Simulation Optimization Approach

The problem presented above is difficult to address using an optimization technique since the objective function and constraints contain stochastic parameters. Simulation would be too time-consuming given the size of the problem. This makes simulation optimization approach preferable, which can evaluate the stochastic parameters and produce good results in reasonable time.

In this thesis, the simulation optimization approach embedded in OptQuest (OptTek Systems, Inc. 2005) is to find a solution for the NORA scheduling problem described above. OptQuest was first developed in 1996 by Glover, Kelly and Lauguna. It searches optimal schedules based on scatter search, tabu search and a neural network accelerator (Lauguna, 1997a). OptQuest will generate a population of candidate solution and then these solutions will be evaluated by corresponding objective function values in each iteration.

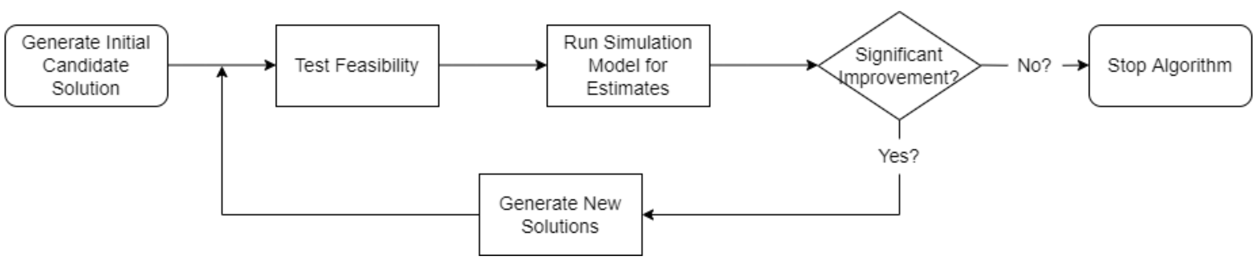

Figure 6. The simulation optimization approach embedded in OptQuest

Figure 6 (adapted from OptQuest Guide, 2017) shows the process of this algorithm. It starts by generating an initial population of reference points or candidate solutions. There must be at least one candidate solution where all the points are among pre-determined lower and upper bounds. These solutions are then tested for whether they are feasible for all the linear constraints. Feasible solutions are evaluated by running the simulation models for enough replications until they all have good estimates of objective function values. OptQuest employs neural network heuristic, which is trained with automatically determined numbers of reference points, to limit the number of calls to the simulation model (Lauguna, 1997b). New candidate solutions are generated using a scatter search heuristic. Two candidate solutions, which are selected based on the quality of their objective function values and the number of iterations they remain in the population, will be served as parent reference point to create four new reference points. The worst parent reference point is replaced by best new reference point, while the other parent reference point will be given a tabu-active status to avoid being selected again as parent reference point for a few subsequent iterations. The population size is automatically adjusted considering the time limit that user has allowed the system to search (Lauguna, 1997b). The process stops when there is no significant improvement in objective function values. The simulation model is developed in Arena 14.0 (Rockwell Software, Inc. 2005). Optquest will then be applied to the model developed earlier to find schedules that aim to minimize the performance measures

The simulation optimization approach is widely adopted in areas such as manufacturing (Haeussler, &Netzer, 2020), allocation (Singh, 2014) and inventory management (Chen et al., 2021). As for surgery scheduling, Liang et al. (2015) built optimization models to find schedules that have best combined scheduling policy by maximizing patient throughput and minimizing patient waiting time. This optimal schedule was then compared to schedules that only optimized single objective in simulation model created by Arena. The approach used in this thesis was established by Klassen and Yoogalingam (2009) as a robust solution method where multiple variables and factors can be accommodated into various problem settings offering more flexibility.

3.4 Data

Anonymous secondary data was obtained from the Discharge Abstract Database (DAD) and National Ambulatory Care Reporting System metadata (NACRS) of the Canadian Institute for

Health Information (CIHI). CIHI is a non-profit organization that collects data from health care institutions across Canada. They provide comparable and actionable data and information that are used to accelerate improvements in health care, health system performance and population health across Canada (CIHI, 2018). The dataset used in this thesis are not public available and they have been approved by Research Ethics Board. They are comprised of elective day surgery records for the period between April 2017 and March 2019. The data elements include a Canadian Classification of Health Interventions (CCI) code that describes the surgery type, date and time when surgery begins and ends, and the anesthetic technique used (e.g., local anesthesia, regional anesthesia and general anesthesia).

3.4.1 Data Cleaning

From the initial data records, the records with missing values or invalid values of Intervention (surgery) Episode Duration were removed from dataset. The data reflects outpatient visits, so procedures with an Admission Date and Discharging Date that are not on the same day were also be eliminated.

The data we asked for are the surgeries with anesthesia procedures. We found that most of these surgeries are surgeries associated with Bladder interventions (1.PM.^^.^^). Based on empirical data in the literature, duration of this type of surgery is not below 25 minutes. Therefore, procedures with a duration below 25 minutes were removed. Considering the mean time and standard deviation, surgery duration above 90 minutes were also eliminated given that major complications for this type of procedure are rare (Costa, 2017). The resulting dataset consisted of 8,526 records for surgeries with an anesthesia component. Summary statistics are given in Table 1, Figure 7 and Figure 8.

Table 1. Summary Statistics for Surgeries

Mean	41.88048
Standard Error	0.151973
Median	38
Mode	30
Standard Deviation	14.03259
Sample Variance	196.9135
Kurtosis	0.855913
Skewness	1.131397
Range	65
Minimum	25
Maximum	90
Sum	357073
Count	8526

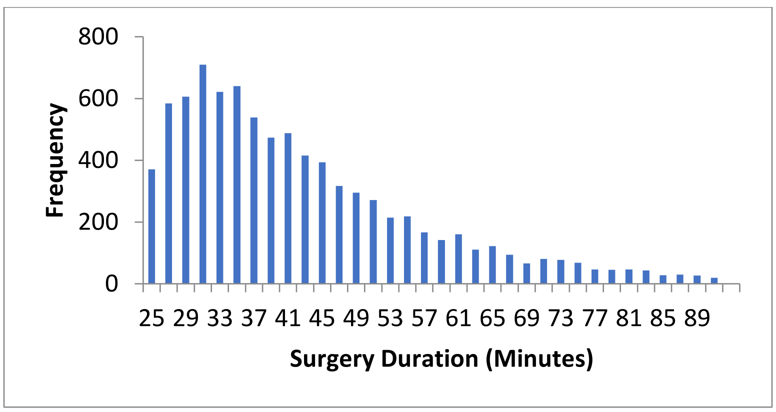

Figure 7. Histogram for Surgeries

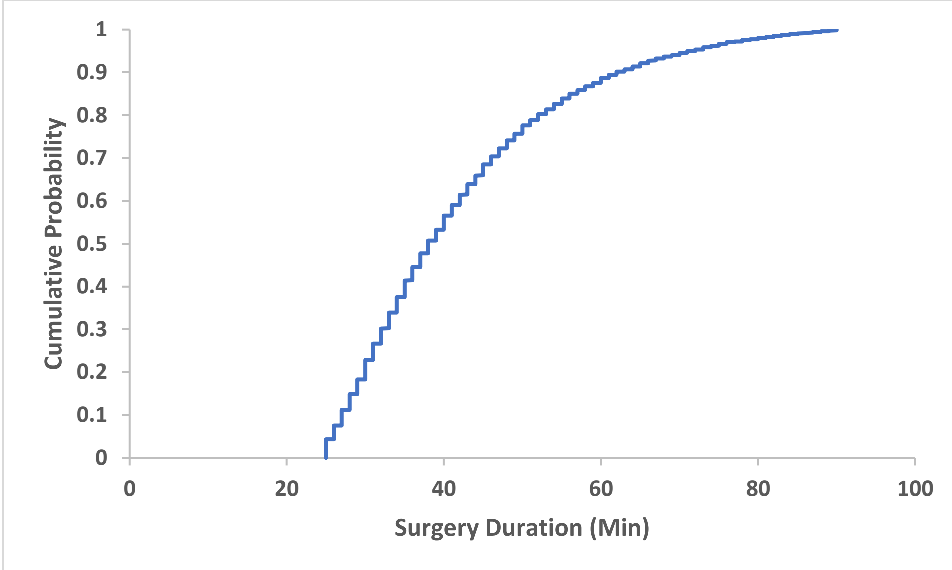

Figure 8. Cumulative Distribution Function for Surgeries

3.4.2 Fitting the data to a Probability Distribution

Surgery durations used in many surgery scheduling studies follow a Lognormal distribution (Jebali & Diabat, 2017; Zhang, Murali, Dessouky, &Belson, 2009). A Lognormal distribution was also found to be a good fit for the data at an $\alpha = 0.05$ level of significance (p-value = 0.087). Therefore, the probability distribution for used in this study is Lognormal with a mean of 42 minutes and a standard deviation of 14 minutes. The literature shows that the anesthesia stage takes up 25% of time in OR on average (Burgette, 2017). By subtracting times for anesthesia portions from the real data, new distributions for the NORA stage and the remaining surgery stage are shown in Table 2.

Table 2. Distributions for anesthesia stage and non-anesthesia stage

	Surgery
Anesthesia stage	LOGN(10.5,3.5)
Non-anesthesia stage	LOGN(31.5,10.5)

3.5 Experimental Design

A few papers (Jebali et al. 2006, Lamiri et al. 2008, Pulido et al. 2014, Zhang et al. 2014) have reported that the opportunity cost of overtime is higher than idle time costs. For example, Jebali et al. (2006) claims that OR overtime costs are 70% higher than idle time costs while Zhang et al. (2014) estimates the ratio for overtime to idle time is 1.5:1. It is reasonable to believe that $1 \leq c_{ot}/c_{it} \leq 2$. We will use the ratio of 1.5 for this research. A set of $c_{it} = \{1,15,50\}$ is used to represent different valuations for surgeon/OR time and resources. Different values for the cost coefficients can be regarded as different goals for hospitals. Since total costs consider benefits from both patient and hospital sides, lower weights of OR idle time and overtime should be considered (i.e., $c_{it} = 1$, $c_{ot} = 1.5$) when hospitals have sufficient resources and patient satisfaction has a higher priority; on the other hand, higher weights of OR idle time and overtime should be considered (e.g., $c_{it} = 50$, $c_{ot} = 75$) when OR resources are limited for patients. This is typically the more realistic scenario facing hospitals.

The session length is set at 420 minutes which allows for the scheduling of ten surgeries based on mean surgery duration. Surgery duration follows a distribution of LOGN (42,14). Three hundred replications are performed for each model.

There are two factors that are further investigated in this thesis. These factors are designed to study the impact of variability in mean surgery duration and differences in the mean surgery duration itself. The first experiment considers different standard deviation for surgeries, which increase the uncertainty associated with completing each procedure. The goal is to determine the impact of an increase in the variability of surgery durations on OR performance with a NORA policy. Standard deviations of 15 and 20 minutes for stage 2-2 and 2-3 are tested. The second experiment considers different mean surgery durations. The NORA policy will be applied to different surgery mean durations and to determine the impact of shorter/longer mean duration on the best NORA schedule. Mean durations of 25, 50 and 75 minutes are tested. The impact of these factors will be tested under scenarios with different session lengths and number of surgery appointments to determine if further insights can be provided under different operating conditions.

4 Results

The Simulation optimization model results are presented in this section. All the models running in OptQuest use 300 replications for comparison. This chapter is organized as follows: Section 4.1 explains the results of the single-OR Basic Model with No NORA policy. Section 4.2 presents the results of the single-OR NORA model. The results from this case are compared to the Basic Model and to show how a NORA policy can improve OR performance. The multi-OR NORA model is not considered because all surgeries are drawn from the same distribution (i.e., are all the same type). To study the effects of different operating conditions, Sections 4.3 and 4.4 provide results for experiments with variations in the distribution parameters for surgery duration. In Section 4.3, different standard deviation values representing the uncertainty level of surgery duration are tested. The purpose of these experiments is to determine the impact of changes in the standard deviation on NORA policy performance. Section 4.4 presents the results of experiments with different mean durations. The performance of NORA policy for shorter and longer mean surgery durations are discussed in this section.

4.1 Basic Model Results: Single-OR Model with No NORA Policy

The Basic Model with no NORA policy is considered in this section. These results provide a basis of comparison for the NORA models to determine how a NORA policy can improve OR efficiency. Table 3 shows the results for the best schedule for the cost coefficients tested. The mean and 95% confidence interval are provided for the performance measures of interest. The percentage change in the mean performance measure when the cost coefficient values increase is provided in parentheses). For the Basic Model, ten surgeries are scheduled during a session length of 420 minutes. All surgery durations are drawn from a Lognormal distribution with a mean of 42 minutes and standard deviation of 14 minutes. WTITOT is the expected total cost.

Table 3. Results for Model with no NORA policy (Basic Model)

Performance Measure	Mean
c_{it} = 1, c_{ot}= 1.5	
Total Waiting Time (min)	70.49±4.76
Total Idle Time (min)	42.33±1.49
Overtime (min)	41.84±1.26
Utilization	0.91±0.00
WTITOT1.5	175.58±5.44
c_{it} = 15, c_{ot}= 22.5 (Percentage compared to c_{it} = 1, c_{ot}= 1.5)	
Total Waiting Time (min)	313.44±10.46 (+344.65%)
Total Idle Time (min)	8.26±0.60 (-80.46%)
Overtime (min)	16.32±1.39 (-60.99%)
Utilization	0.98±0.00 (+7.69%)
WTIT15OT22.5	804.76±38.26 (+358.34%)
c_{it} =50, c_{ot}= 75 (Percentage compared to c_{it} = 15, c_{ot}= 22.5)	
Total Waiting Time (min)	679.68±12.57 (+122.59%)
Total Idle Time (min)	0.85±0.21 (-89.71%)
Overtime (min)	13.60±1.32 (-16.67%)
Utilization	0.99±0.00 (+1.02%)
WTIT50OT75	1742.45±106.86 (+116.52%)

As shown in Table 3, when c_{it} = 1, c_{ot}= 1.5, mean total waiting time, total idle time and overtime are 70.49±4.76, 42.33±1.49 and 41.84±1.26 minutes when expected total costs are lowest. It means that each patient will wait an average of 7.05 minutes for their surgeries. OR utilization is 91% under this situation since patient waiting time has a higher priority than other situations.

Under the condition of c_{it} = 15, c_{ot}= 22.5, mean total waiting times, total idle time and overtime are 313.44±10.46, 8.26±0.60 and 16.32±1.39 minutes when expected total costs are lowest. Average waiting time for each patient is 31.34 minutes. With increased cost of OR idle time and overtime, waiting time for patients has increased 344.65% while OR idle time and overtime decreased by 80.49% and 60.99%, respectively. When c_{it} = 50, c_{ot}= 75, mean total waiting times, total idle time and overtime are 679.68±12.57, 0.85±0.21 and 13.60±1.32 minutes when expected total costs are lowest. Average waiting time for each patient increases to 67.97 minutes, which is 122.59% higher; average idle time decreases to 0.85 minutes and overtime decreases to 13.60 minutes, which are 89.71% and 16.67% lower. As expected, the patient waiting time measure deteriorates significantly when OR resources are weighted more heavily.

The results show that with the increase for the weights of OR idle time and overtime, patient waiting time has increased relatively, which can have a negative impact on patient satisfaction; on the other hand, OR idle time and overtime have significantly decreased, which is positive for hospitals considering how costly OR resources are.

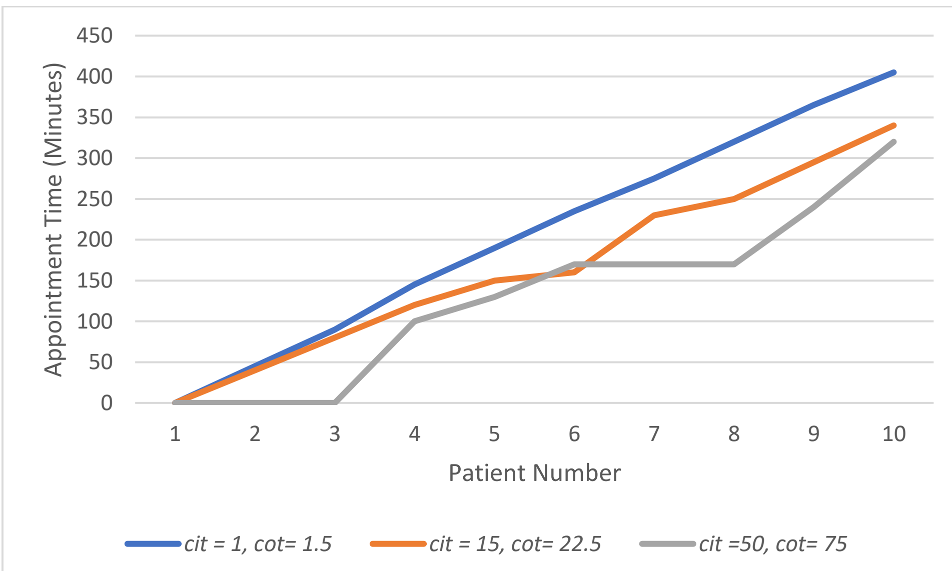

Figure 9. OR schedule for Basic Model

Figure 9 shows the best schedules for the Basic Model for the three cost coefficient settings. For c_{it} = 1 and c_{ot}= 1.5, patients are scheduled to arrive separately with an interval close to their mean surgery duration of 42 minutes. For c_{it} = 15, and c_{ot}= 22.5, some patients are scheduled with a shorter interval between appointments. In addition, the last surgery is scheduled earlier than for lower weights. This results from OR resources being more costly. In order to minimize idle time and overtime, patients are scheduled more closely together in case a surgery ends earlier than expected. For c_{it} = 50, and c_{ot}= 75, most patients are scheduled in groups to arrive at the same time. For example, Surgeries 1-3 and 6-8 are triple booked at the same time and the last surgery is scheduled 100 minutes before the end of the session. Surgeries are scheduled even more closely together to minimize the likelihood that the OR experiences idle time and overtime which are the costliest under this scenario. It is not ideal for hospitals to double-book or triple-book appointments assuming all patients arrive on time. Hospitals can schedule patients in a short interval of 5-10 minutes to avoid these problems.

4.2 NORA Model Results: Single-OR Model with NORA

A NORA policy allows part of the pre-incision stage to be performed outside OR, which reduces the surgery duration in OR. In this section, three NORA options are presented: (1) A policy where ten surgeries are performed in a 420 minute session length; (2) A policy where the same number of surgeries, ten surgeries, are performed each in a shorter session length of 315 minutes and (3) A policy where more surgeries, thirteen surgeries, are performed in a 420 minute session. For Option 2, the mean of each surgery is 31.5 minutes (See Table 1), which leads to a session length of 315 minutes. For Option (3), a session length of 420 minutes can accommodate 13 surgeries at most. This will allow for a comparison of OR performance when the conditions change one at a time. The results for each NORA option are presented in Sections 4.2.1-4.2.3 followed by a comparison of each option with the results from the Basic Model in Section 4.2.4.

4.2.1 NORA Model Option 1: Ten Surgery Appointments in a 420 Minute Session

We first test a NORA policy using the same session length and number of surgery appointments as the Basic Model (i.e., ten appointments in a 420-minute session). The results for this option are displayed in Table 4 for the three cost coefficient settings tested for the Basic Model.

Table 4. Results for NORA Model Option 1

Performance Measure	Mean
c_{it} = 1, c_{ot}= 1.5	
Total Waiting Time (min)	43.89±1.87
Total Idle Time (min)	100.38±1.80
Overtime (min)	4.21±0.57
Utilization	0.75±0.00
WTITOT1.5	150.59±2.07
c_{it} = 15, c_{ot}= 22.5 (Percentage compared to c_{it} = 1, c_{ot}= 1.5)	
Total Waiting Time (min)	173.87±8.39 (+296.15%)
Total Idle Time (min)	9.91±0.83 (-90.13%)
Overtime (min)	0.11±0.15 (-97.38%)
Utilization	0.97±0.00 (+29.33%)
WTIT15OT22.5	325.12±11.00 (+115.90%)
c_{it} =50, c_{ot}= 75 (Percentage compared to c_{it} = 15, c_{ot}= 22.5)	
Total Waiting Time (min)	294.06±10.13 (+69.13%)
Total Idle Time (min)	2.78±0.41 (-33.97%)
Overtime (min)	0.11±0.15 (+0.00%)
Utilization	0.99±0.00 (+2.06%)
WTIT50OT75	441.76±17.89 (+35.88%)

Under the condition of c_{it} = 1, c_{ot}= 1.5, mean total waiting times, total idle time and overtime are 43.89±1.87, 100.38±1.80 and 4.21±0.57 minutes. OR utilization is only 75% under this situation due to the large amount of OR idle time resulting from NORA. When c_{it} = 15, c_{ot}= 22.5, mean total waiting times, total idle time and overtime are 188.55±8.41, 9.60±0.81 and 0.11±0.15 minutes when expected total costs are lowest. OR idle time has decreased 90.13% while average patient waiting time has increased 296.13%. Under the condition of c_{it} = 50, c_{ot}= 75, mean total waiting times, total idle time and overtime are 294.06±10.13, 2.78±0.41 and 0.11±0.15

minutes when expected total costs are lowest. Average total patient waiting time has increased 69.13% and total idle time has decreased 33.97%.

When compared to the results for the Basic Model, applying a NORA policy has positive impacts on OR efficiency because performance measures for all three settings of coefficients have improved. The results of the NORA Model differ from the Basic Model because total surgery durations in the OR are shorter, which leads to a reduction in patient waiting time and OR overtime, but an increase in OR idle time since the OR is not fully utilized. This option may be used in hospitals that experience a high number of emergency arrivals and need to leave room in the schedule to accommodate these patients.

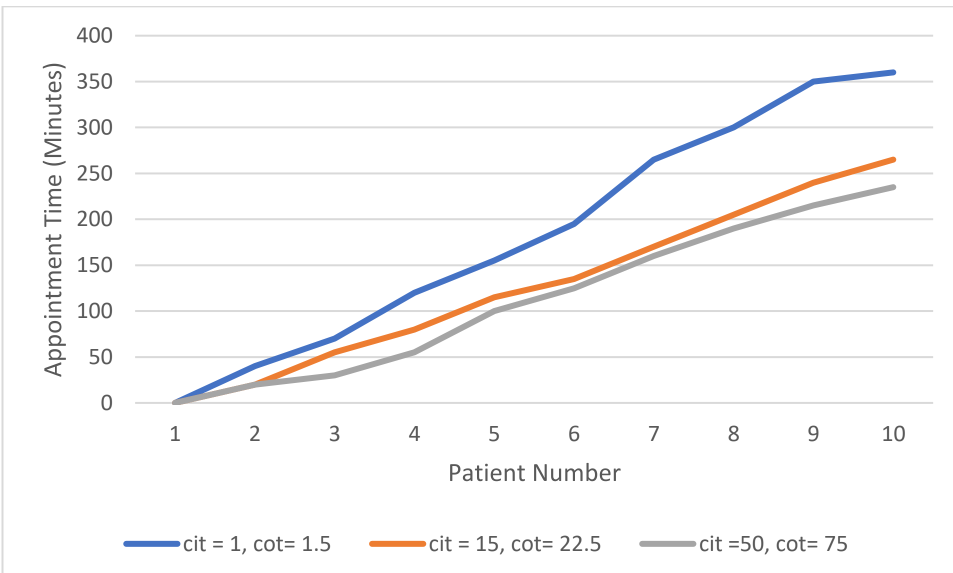

Figure 10. OR schedule for NORA Model Option 1

Figure 10 shows the best OR schedule for NORA Model Option 1. Since there is sufficient time available in OR, all the patients are spaced apart and the last surgery with higher weights on OR idle time and overtime is scheduled much earlier than the last surgery with lower weights. For example, the last surgery for c_{it} = 50, c_{ot}= 75 is scheduled 125 minutes earlier than c_{it} = 1, c_{ot}= 1.5. However, this option is unrealistic for a hospital because it does not fully utilize the resources of the OR. In Sections 4.2.2 and 4.2.3, two more realistic options for implementing NORA are presented.

4.2.2 NORA Model Option 2: Ten Surgery Appointments in a 315 Minute Session

For comparison purposes, we also test a NORA policy with a shorter session length of 315 minutes and ten surgery appointments. With reduced surgery durations, ten surgery appointments within a shorter session length are explored to detect how NORA policy can improve OR efficiency when the OR is fully utilized. The results are displayed in Table 5.

Table 5. Results for NORA Model Option 2

Performance Measure	Mean
c_{it} = 1, c_{ot}= 1.5	
Total Waiting Time (min)	58.78±4.42
Total Idle Time (min)	41.16±1.49
Overtime (min)	40.45±1.09
Utilization	0.88±0.00
WTITOT1.5	160.61±4.76
c_{it} = 15, c_{ot}= 22.5 (Percentage compared to c_{it} = 1, c_{ot}= 1.5)	
Total Waiting Time (min)	300.67±9.14 (+411.52%)
Total Idle Time (min)	5.77±0.61 (-85.98%)
Overtime (min)	13.77±1.26 (-65.96%)
Utilization	0.98±0.00 (+11.36%)
WTIT15OT22.5	696.89±33.52 (+333.90%)
c_{it} =50, c_{ot}= 75 (Percentage compared to c_{it} = 15, c_{ot}= 22.5)	
Total Waiting Time (min)	599.19±10.83 (+99.28%)
Total Idle Time (min)	2.86±0.49 (-50.43%)
Overtime (min)	12.82±1.25 (-6.90%)
Utilization	0.99±0.00 (+1.02%)
WTIT50OT75	1703.87±98.62 (+144.50%)

Table 5 shows that when c_{it} = 1, c_{ot}= 1.5, mean total waiting times, total idle time and overtime are 58.78±4.42, 41.16±1.49 and 40.45±1.09 minutes when expected total costs are lowest. Average waiting time for each patient is 5.88 minutes. Patient waiting time is still low while OR idle time is slightly longer than overtime. Under the condition of c_{it} = 15, c_{ot}= 22.5, mean total waiting times, total idle time and overtime are 300.67±9.14, 5.77±0.61 and 13.77±1.26 minutes when expected total costs are lowest. Average waiting time for each patient will be 30.07 minutes. Similar to the results for the Basic Model, waiting time for patients has increased 411.52% while OR idle time and overtime decreased 85.98% and 65.96%. Under the condition of c_{it} = 50, c_{ot}= 75, mean total waiting times, total idle time and overtime are 599.19±10.83, 2.86±0.49 and 12.82±1.25 minutes when expected total costs are lowest. Average waiting time for each patient increases to 59.92 minutes. Average total patient waiting time has increased 99.28% and total idle time has decreased 50.43%. The results are close to the results for Option 1 since the sum of mean surgery durations for both settings are equal to the session length with the same number of ten surgeries. Patient waiting time is better in Option 1 since appointments are scheduled within a longer session.

The results under this setting are consistent with the results from the Basic Model with No NORA Policy, where patient waiting time increases, and OR idle time and overtime decreases with the increased weights of OR idle time and overtime. This means under this setting, hospitals can still consider lower weights of OR idle time and overtime (i.e., c_{it} = 1, c_{ot}= 1.5) when they have sufficient resources and consider higher weights of OR idle time and overtime (i.e., c_{it} = 50, c_{ot}= 75) when OR resources are limited for patients.

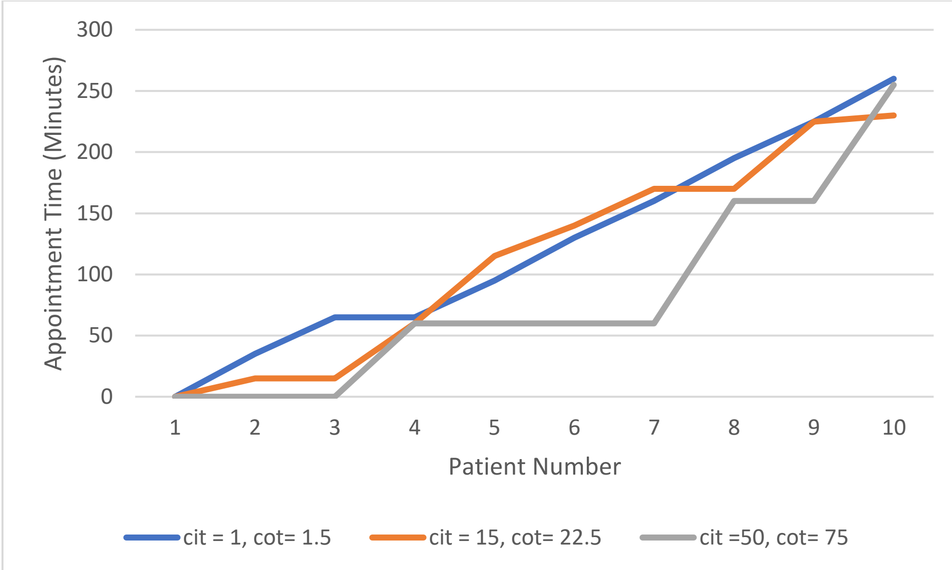

Figure 11. OR schedule for NORA Model Option 2

Figure 11 shows the best OR schedule for NORA Model Option 2 with a session length of 315 minutes and ten surgeries. For c_{it} = 1, c_{ot}= 1.5, patients are scheduled to arrive separately with an interval close to their mean surgery duration. For c_{it} = 15, c_{ot}= 22.5, patients are scheduled with a shorter interval. For c_{it} = 50, c_{ot}= 75, there are instances of multiple patients booked at the same time. This schedule differs from the one above with a 420 minute session length in that patients are scheduled closer to reduce the likelihood of OR being idle or working overtime since there are no longer sufficient OR time slots available compared to NORA Model Option 1.

4.2.3 NORA Model Option 3: Thirteen Surgery Appointments in a 420 Minute Session

In this section, the results for a NORA policy and a larger number of surgery appointments are presented. This option captures the case where a hospital can increase the number for surgery appointments when implementing a NORA policy. A set of same cost coefficients are used for comparing results. This scenario considers a schedule with 13 surgeries of same type and a session length of 420 minutes. The results are displayed in Table 6.

Table 6. Results for NORA Model Option 3

Performance Measure	Mean
c_{it} = 1, c_{ot}= 1.5	
Total Waiting Time (min)	102.64±6.04
Total Idle Time (min)	54.94±1.78
Overtime (min)	43.65±1.17
Utilization	0.88±0.00
WTITOT1.5	223.05±6.18
c_{it} = 15, c_{ot}= 22.5 (Percentage compared to c_{it} = 1, c_{ot}= 1.5)	
Total Waiting Time (min)	697.33±11.75 (+579.39%)
Total Idle Time (min)	12.53±0.93 (-77.19%)
Overtime (min)	12.79±1.27 (-70.70%)
Utilization	0.96±0.00 (+9.09%)
WTIT15OT22.5	1172.95±35.97 (+425.87%)
c_{it} =50, c_{ot}= 75 (Percentage compared to c_{it} = 15, c_{ot}= 22.5)	
Total Waiting Time (min)	746.93±15.31 (+7.11%)
Total Idle Time (min)	2.29±0.36 (-81.72%)
Overtime (min)	10.24±1.20 (-19.94%)
Utilization	0.99±0.00 (+3.13%)
WTIT50OT75	1629.69±98.73 (+38.94%)

As shown in Table 6, when c_{it} = 1, c_{ot}= 1.5, mean total waiting times, total idle time and overtime are 102.64±6.04, 54.94±1.78 and 43.65±1.17 minutes when expected total costs are lowest. Average waiting time for each patient is 7.89 minutes. OR idle time is 11.29 minutes longer than OR overtime. Under the condition of c_{it} = 15, c_{ot}= 22.5, mean total waiting times, total idle time and overtime are 697.33±11.75, 12.53±0.93 and 12.79±1.27 minutes when expected total costs are lowest. Average waiting time for each patient is 53.64 minutes; Patient waiting time has increased by 579.39% while OR idle time and overtime decrease by 77.19% and 70.70%. Under the condition of c_{it} = 50, c_{ot}= 75, mean total waiting times, total idle time and overtime are 746.93±15.31, 2.29±0.36 and 10.24±1.20 minutes when expected total costs are lowest. Average waiting time for each patient increases to 57.46 minutes. Total idle time has decreased 81.72% and overtime has decreased by 19.94%. The results are different from Option 1 because there are more surgeries to be performed in OR. It adds more duration uncertainty for scheduling, which has negative impacts on OR performance.

The results under these settings are still consistent with the results from model of no NORA policy, where patient waiting time increases, and OR idle time and overtime decreases with the increased weights of OR idle time and overtime. The same conclusion from 4.2.2 can still be applied to this setting, where hospitals can consider lower weights of OR idle time and overtime (i.e., c_{it} = 1, c_{ot}= 1.5) when they have sufficient resources and consider higher weights of OR idle time and overtime (i.e., c_{it} = 50, c_{ot}= 75) when OR resources are limited for patients. However, NORA significantly improves all performance measures when compared to the Basic Model.

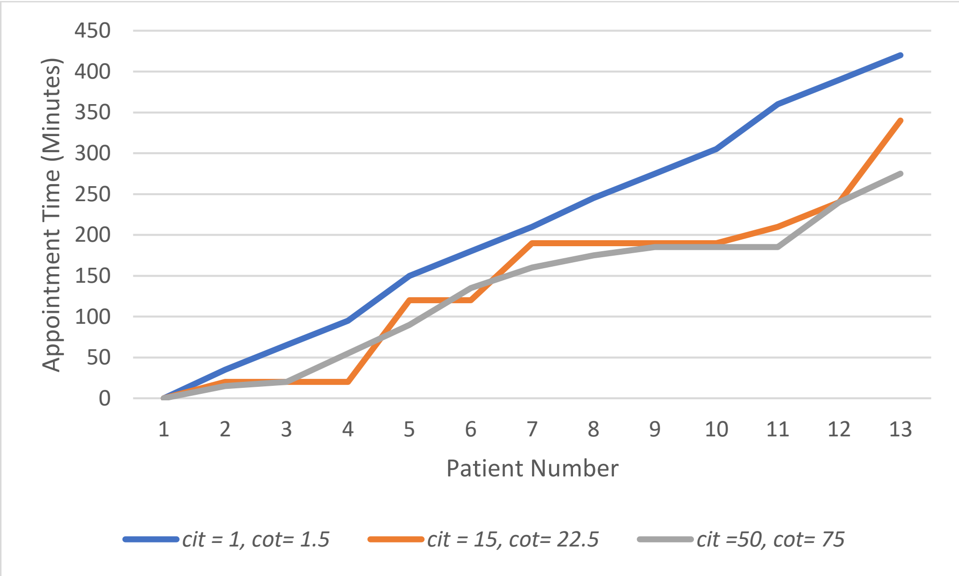

Figure 12. OR schedule for NORA Model Option 3

Figure 12 shows the best OR schedule for the NORA Model Option 3 with a session length of 420 minutes and 13 surgeries. For c_{it} = 1, c_{ot}= 1.5, patients are scheduled to arrive separately with an interval close to their mean surgery duration. For c_{it} = 15, c_{ot}= 22.5, patients are scheduled mostly in groups, while the last surgery is scheduled much before end of session. For c_{it} = 50, c_{ot}= 75, patients are scheduled to arrive in short intervals. The main differences for this schedule from

Basic Model are when weights of OR idle time and overtime are higher, more surgeries are scheduled in groups or last surgery is scheduled much earlier. For example, in the schedule of c_{it} = 15, c_{ot}= 22.5, Surgeries 2-4, 5-6 and 7-10 are booked at the same time; while in the schedule of c_{it} = 50, c_{ot}= 75, the last surgery is scheduled 45 minutes earlier than the one in Basic Model to reduce the likelihood of costly OR overtime. This implies that an OR manager may have more flexibility in scheduling appointments with a NORA policy.

4.2.4 Comparison of Results for the Basic Model and the NORA Models

Table 7 provides a summary of the key results of the Basic and NORA models. According to ANOVA results (see Appendix Table A1-A4), there is a significant decrease in expected total cost between the Basic Model and each of the NORA Models.

Table 7. Comparison of results for Basic Model and NORA Models

Performance Measure		Basic Model	NORA Model Option 1	NORA Model Option 2	NORA Model Option 3
c_{it}=1, c_{ot}=1.5	Total Waiting Time	70.49±4.76	43.89±1.87	58.78±4.42	102.64±6.04
	Total Idle Time	42.33±1.49	100.38±1.80	41.16±1.49	54.94±1.78
	Overtime	41.84±1.26	4.21±0.57	40.45±1.09	43.65±1.17
	Utilization	0.91±0.00	0.75±0.00	0.88±0.00	0.88±0.00
	WTITOT1.5	175.58±5.44	150.59±2.07	160.61±4.76	223.05±6.18
c_{it}=15, c_{ot}=22.5	Total Waiting Time	313.44±10.46	173.87±8.39	300.67±9.14	697.33±11.75
	Total Idle Time	8.26±0.60	9.91±0.83	5.77±0.61	12.53±0.93
	Overtime	16.32±1.39	0.11±0.15	13.77±1.26	12.79±1.27
	Utilization	0.98±0.00	0.97±0.00	0.98±0.00	0.96±0.00
	WTIT15OT22.5	804.76±38.26	325.12±11.00	696.89±33.52	1172.95±35.97
c_{it}=50, c_{ot}=75	Total Waiting Time	679.68±12.57	294.06±10.13	599.19±10.83	746.93±15.31
	Total Idle Time	0.85±0.21	2.78±0.41	2.86±0.49	2.29±0.36
	Overtime	13.60±1.32	0.11±0.15	12.82±1.25	10.24±1.20
	Utilization	0.99±0.00	0.99±0.00	0.99±0.00	0.99±0.00
	WTIT50OT75	1742.45±106.86	441.76±17.89	1703.87±98.62	1629.69±98.73

Comparing the Basic Model and the NORA Model Option 1, for the three sets of cost coefficients values, patient waiting time and overtime are lower while OR idle time is higher for

NORA Model Option 1. ANOVA results (See Appendix Table A2-A4) show that there are significant decreases in the expected total costs for all three settings of c_{it} and c_{ot}, which means NORA can significantly improve OR efficiency.

The results for the Basic Model and the NORA model Option 2 for all three settings of c_{it} and c_{ot}, show patient waiting time, OR idle time and overtime are close for these two models. ANOVA results (See Appendix Table A2-A4) show that there are no significant differences or significant decrease for performance measure of expected total cost, which means that NORA policy saves OR time without significantly increasing expected total costs. This result shows that NORA policy has a better performance considering the session length of NORA model.

The results are similar when comparing the Basic Model and the NORA model Option 3. For c_{it}=1, c_{ot}=1.5, patient waiting time, OR idle time and overtime are all higher for the NORA model Option 3. However, the hospital is able to schedule a larger number of surgeries under this option. ANOVA results (See Appendix Table A2) show that the Basic Model has a significantly lower expected total cost. For the setting of c_{it}=15, c_{ot}=22.5, patient waiting time and OR overtime are lower while OR idle time is slightly higher for the NORA model. ANOVA results (See Appendix Table A3) indicate that the Basic Model has a significantly lower expected total cost. For the setting of c_{it}=50, c_{ot}=75, patient waiting time and OR overtime are lower while OR idle time is slightly higher for NORA model. According to ANOVA results (See Appendix Table A4), there is no significant differences for performance measure of expected total cost. Performing more surgeries within same session length definitely has a negative impact on OR efficiency, as shown for the setting of c_{it}=1, c_{ot}=1.5 and c_{it}=15, c_{ot}=22.5, average cost per surgery is much lower for these two coefficients settings. On the other hand, when coefficients of OR idle time and overtime are high, NORA policy shows no significant difference not only on average expected total costs per surgery but also on expected total costs as a whole measure. This implies that when OR resources are more costly, a NORA policy can be beneficial in terms of improving efficiency. This policy can also provide an OR manager more flexibility in terms of scheduling surgery appointments as well as accommodating emergency patients if necessary.

4.3 Experiments with Variation in Standard Deviation of Surgery Duration

Variation of surgery durations can be different due to proficiency of surgeons or even hospital settings. Standard deviations are the measures that indicate these variations. They are one of the key factors for improving OR efficiency because a smaller standard deviation associated with surgery duration means a more predictable surgery duration. This will make it easier for managers to schedule surgeries and produce better results. This experiment aims to explore how a NORA policy performs with larger standard deviation values for surgery duration. The standard deviation generated through this dataset is 14 minutes. Since we assume that 25% of the time is anesthesia stage times, the standard deviation used for non-anesthesia stage is 10.5 minutes (see Table 1). In this section, Standard deviations of 15 minutes and 20 minutes for the scenarios of same number of surgery appointments or same session length are tested. Results for the Basic Model and Options 2 and 3 of the NORA Model are presented in Sections 4.3.1-4.3.3. Option 1, which schedules ten appointments in a 420 minute session, is not considered since it does not fully utilize the OR session. An overall comparison of the results is provided in Section 4.3.4.

4.3.1 Basic Model with Larger Standard Deviation

The Basic Model (no NORA), which consists of ten surgeries and a 420 minute session length, is first analyzed. Since non-anesthesia stages have the standard deviation values of 15 and 20 minutes, the Basic Models use approximated values of the standard deviation of 18.5 (15+3.5) and 23.5 (20+3.5) minutes. The results for the mean of each performance measure of interest are displayed in Table 8.

Table 8. Results for Basic Model with standard deviation of 15 minutes (STD1) and 20 minutes (STD2)

Performance Measure		Basic Model	Basic Model STD1	Basic Model STD2
c_{it}=1, c_{ot}=1.5	Total Waiting Time	70.49±4.76	119.61±8.96	174.97±12.96
	Total Idle Time	42.33±1.49	46.08±1.89	53.17±2.36
	Overtime	41.84±1.26	45.29±1.85	52.11±2.58
	Utilization	0.91±0.00	0.90±0.00	0.88±0.01
	WTITOT1.5	175.58±5.44	233.62±9.89	306.31±14.45
c_{it}=15, c_{ot}=22.5 (Percentage compared to c_{it} = 1, c_{ot}= 1.5)	Total Waiting Time	313.44±10.46 (+344.65%)	574.65±15.34 (+380.52%)	602.37±29.72 (+244.27%)
	Total Idle Time	8.26±0.60 (-80.46%)	6.62±0.76 (-85.63%)	9.30±1.03 (-82.51%)
	Overtime	16.32±1.39 (-60.99%)	19.82±1.89 (-56.24%)	25.43±2.58 (-21.20%)
	Utilization	0.98±0.00 (+7.69%)	0.98±0.00 (+8.89%)	0.98±0.00 (+11.36%)
	WTIT15OT22.5	804.76±38.26 (+358.34%)	1119.72±52.26 (+379.29%)	1313.91±70.43 (+328.95%)
c_{it}=50, c_{ot}=75 (Percentage compared to c_{it} = 15, c_{ot}= 22.5)	Total Waiting Time	679.68±12.57 (+122.59%)	624.22±17.28 (+8.63%)	681.21±22.40 (+13.88%)
	Total Idle Time	0.85±0.21 (-89.71%)	2.33±0.49 (-68.97%)	3.08±0.46 (-66.88%)
	Overtime	13.60±1.32 (-16.67%)	18.75±1.89 (-5.40%)	24.86±2.58 (-2.24%)
	Utilization	0.99±0.00 (+1.02%)	0.99±0.00 (+1.02%)	0.99±0.00 (+1.02%)
	WTIT50OT75	1742.45±106.86 (+116.52%)	2147.15±151.12 (+91.76%)	2699.82±206.58 (+105.48%)

As expected, Table 8 shows that all performance measures deteriorate when the standard deviation increases. For standard deviation = 15 minutes (Basic Model STD1), under the condition of c_{it} = 1, c_{ot}= 1.5, mean total waiting times, total idle time and overtime are 119.61±8.96, 46.08±1.89 and 45.29±1.85 minutes when expected total costs are lowest. Average waiting time for each patient is 11.96 minutes. Under the condition of c_{it} = 15, c_{ot}= 22.5, mean total waiting times, total idle time and overtime are 574.65±15.34, 6.62±0.76 and 19.82±1.89 minutes when expected total costs are lowest. Average waiting time for each patient will be 57.47 minutes. Waiting time for patients has increased 380.52% while OR idle time and overtime decreased 85.63% and 56.24%. Under the condition of c_{it} = 50, c_{ot}= 75, mean total waiting times, total idle time and overtime are 624.22±17.28, 2.33±0.49 and 18.75±1.89 minutes when expected total costs are lowest. Average waiting time for each patient increases to 62.42 minutes. Total idle time is 68.97% shorter while patient waiting time is 8.63% longer. The results show that larger standard deviation has a negative impact on OR performance for the Basic Model due to higher uncertainty.

For standard deviation = 20 minutes (Basic Model STD2), under the condition of c_{it} = 1, c_{ot}= 1.5, mean total waiting times, total idle time and overtime are 174.97±12.96, 53.17±2.36 and 52.11±2.58 minutes when expected total costs are lowest. Average waiting time for each patient is 17.50 minutes. Patient waiting time is still low while OR idle time is longer than overtime. Under the condition of c_{it} = 15, c_{ot}= 22.5, mean total waiting times, total idle time and overtime are 602.37±29.72, 9.30±1.03 and 25.43±2.58 minutes when expected total costs are lowest. Average waiting time for each patient will be 60.24 minutes. Patient waiting time for patients has increased 244.27% while OR idle time and overtime have decreased 82.51% and 21.20%. Under the condition of c_{it} = 50, c_{ot}= 75, mean total waiting times, total idle time and overtime are 681.21±22.40, 3.08±0.46 and 24.86±2.58 minutes when expected total costs are lowest. Average waiting time for each patient increases to 68.12 minutes. Patient waiting time increases 13.88% while OR idle time and overtime decrease by 66.88% and 2.24%. The results are consistent with previous findings where larger standard deviation contributes to higher uncertainty, which produces even worse results than the model above.

Comparing results of the Basic Model with different standard deviations, all the performance measures including waiting time, OR idle time, overtime and expected total costs become worse with the increase of standard deviation. This shows the hospitals that if they can create an environment where the durations of surgery processes are more predictable, they are more likely to have better performed OR systems.

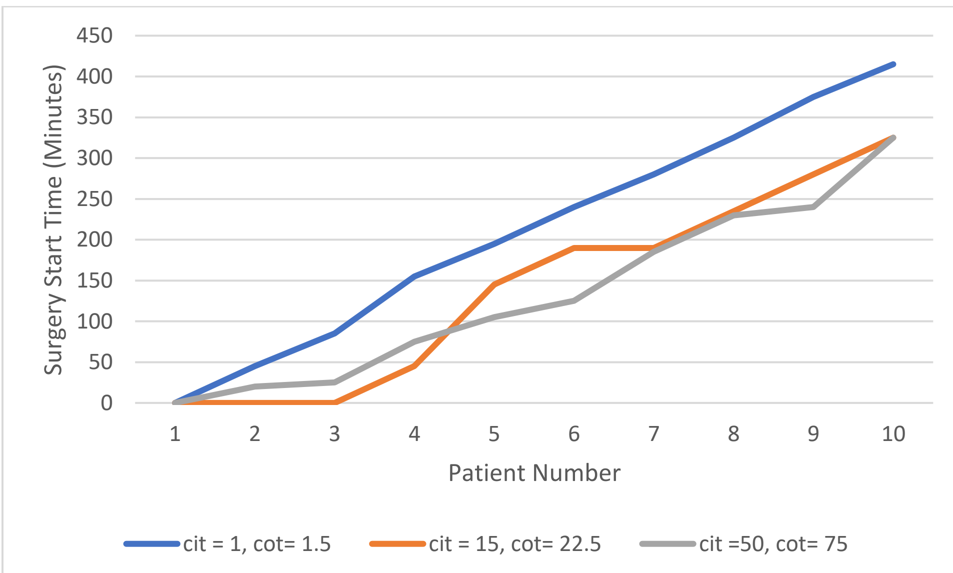

Figure 13. OR schedule for Basic Model STD1

Figure 13 shows the best OR schedule for the Basic Model STD1. For c_{it} = 1, c_{ot}= 1.5, surgeries are scheduled to arrive separately with an interval close to their mean surgery duration. For c_{it} = 15, c_{ot}= 22.5, first three surgeries are scheduled in a group, while the last surgery is scheduled 90 minutes earlier. For c_{it} = 50, c_{ot}= 75, surgeries are scheduled to arrive in shorter intervals. Compared to the Basic Model, surgeries are scheduled more closely clustered together with the last appointment scheduled well before the end of the session.

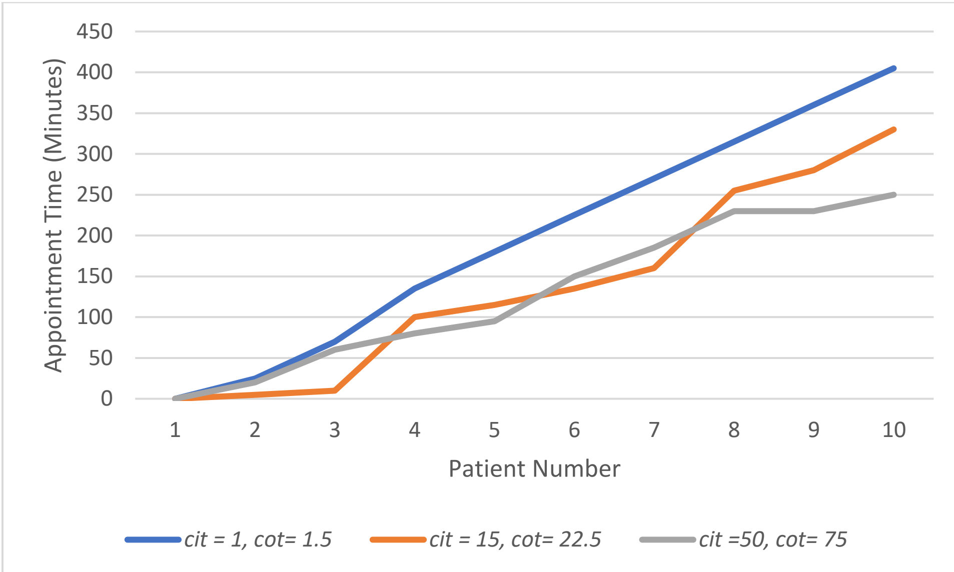

Figure 14. OR schedule for Basic Model STD2

Figure 14 shows the best OR schedule for the Basic Model STD2. For c_{it} = 1, c_{ot}= 1.5, patients are scheduled to arrive separately with an interval close to their mean surgery duration. For c_{it} = 15, c_{ot}= 22.5, patients are scheduled with a shorter interval. For c_{it} = 50, c_{ot}= 75, patients are scheduled to arrive in an even shorter interval, while the last surgery is scheduled earliest among three settings. Compared to the Basic Model, main difference is the last surgery scheduled time, which is 10 and 70 minutes earlier than the last surgery scheduled in Basic Model. The appointment intervals are shorter and the last appointment is scheduled well before the end of the session to reduce the possibility of excessive overtime.

4.3.2 NORA Model Option 2 with Larger Standard Deviation: Ten Surgery Appointments in a 315 Minute Session

In this section, a NORA model scheduling ten surgeries within a 315 minute session (Option 2) is examined. The results are displayed in Table 9. For standard deviation = 15 minutes (NORA Option 2 STD1), under the condition of c_{it} = 1, c_{ot}= 1.5, mean total waiting times, total idle time and overtime are 102.07±7.73, 48.70±1.90 and 47.70±1.77 minutes when expected total costs are lowest. Average waiting time for each patient is 10.21 minutes. Under the condition of c_{it} = 15, c_{ot}= 22.5, mean total waiting times, total idle time and overtime are 524.65±14.22, 6.62±0.81 and 18.63±1.85 minutes when expected total costs are lowest. Average waiting time for each patient is 52.47 minutes. With the increase of idle time and overtime coefficients, patient waiting time increases by 414.01% while OR idle time and overtime decrease 86.41% and 60.94%. Under the condition of c_{it} = 50, c_{ot}= 75, mean total waiting times, total idle time and overtime are 536.53±14.31, 3.99±0.52 and 18.80±1.86 minutes when expected total costs are lowest. Average waiting time for each patient increases to 53.65 minutes. All three performance measures are similar to those from the previous setting. The results show that a larger standard deviation still has a negative impact on OR performance in a NORA policy setting due to higher uncertainty.

For standard deviation = 20 minutes (NORA Option 2 STD2), under the condition of c_{it} = 1, c_{ot}= 1.5, mean total waiting times, total idle time and overtime are 149.28±11.71, 57.18±2.29 and 55.91±2.57 minutes when expected total costs are lowest. Average waiting time for each patient is 14.93 minutes. Under the condition of c_{it} = 15, c_{ot}= 22.5, mean total waiting times, total idle time and overtime are 558.13±18.54, 10.53±1.12 and 25.12±2.56 minutes when expected total costs are lowest. Average waiting time for each patient will be 55.81 minutes. Patient waiting time for patients increases 273.88% while OR idle time and overtime decreases 81.58% and 55.07%.

Under the condition of c_{it} = 50, c_{ot}= 75, mean total waiting times, total idle time and overtime are 732.52±20.33, 2.38±0.49 and 24.07±2.55 minutes when expected total costs are lowest. Average waiting time for each patient increases to 73.25 minutes. Patient waiting time increases 31.25% while OR idle time and overtime decrease 77.40% and 4.18%. The results are consistent with previous findings because of higher uncertainty from larger standard deviation.

Table 9. Results for NORA Model Option 2 with standard deviation of 15 minutes (STD1) and 20 minutes (STD2)

Performance Measures		NORA Model Option 2	NORA Model Option 2 STD1	NORA Model Option 2 STD2
c_{it}=1, c_{ot}=1.5	Total Waiting Time	58.78±4.42	102.07±7.73	149.28±11.71
	Total Idle Time	41.16±1.49	48.70±1.90	57.18±2.29
	Overtime	40.45±1.09	47.70±1.77	55.91±2.57
	Utilization	0.88±0.00	0.86±0.01	0.84±0.01
	WTITOT1.5	160.61±4.76	222.32±8.61	290.33±13.34
c_{it}=15, c_{ot}=22.5 (Percentage compared to c_{it} = 1, c_{ot}= 1.5)	Total Waiting Time	300.67±9.14 (+411.52%)	524.65±14.22 (+414.01%)	558.13±18.54 (+273.88%)
	Total Idle Time	5.77±0.61 (-85.98%)	6.62±0.81 (-86.41%)	10.53±1.12 (-81.58%)
	Overtime	13.77±1.26 (-65.96%)	18.63±1.85 (-60.94%)	25.12±2.56 (-55.07%)
	Utilization	0.98±0.00 (+11.36%)	0.98±0.00 (+13.95%)	0.96±0.00 (+14.29%)
	WTIT15OT22.5	800.13±42.79 (+398.18%)	1043.26±49.72 (+369.26%)	1281.40±67.98 (+341.36%)
c_{it}=50, c_{ot}=75 (Percentage compared to c_{it} = 15, c_{ot}= 22.5)	Total Waiting Time	599.19±10.83 (+99.28%)	536.53±14.31 (+2.26%)	732.52±20.33 (+31.25%)
	Total Idle Time	2.86±0.49 (-50.43%)	3.99±0.52 (-39.73%)	2.38±0.49 (-77.40%)
	Overtime	12.82±1.25 (-6.90%)	18.80±1.86 (+0.91%)	24.07±2.55 (-4.18%)
	Utilization	0.99±0.00 (+1.02%)	0.99±0.00 (+1.02%)	0.99±0.00 (+3.13%)
	WTIT50OT75	1703.87±98.62 (+112.95%)	2146.23±146.02 (+105.72%)	2656.28±203.04 (+107.30%)

With a NORA policy, a larger standard deviation still has a negative impact on overall OR performance. The results are consistent with basic model with larger standard deviations. It means NORA policy cannot offset the effect of more surgery duration uncertainty.

Figure 15 shows the OR schedule for NORA Model Option 2 STD1. For c_{it} = 1, c_{ot}= 1.5, surgeries are scheduled to arrive separately with an interval close to their mean surgery duration. For c_{it} = 15, c_{ot}= 22.5 and c_{it} = 50, c_{ot}= 75, surgeries are scheduled to arrive in groups of three or four, while the last surgery is scheduled around 60 minutes earlier than lower weights. Larger standard deviation means higher uncertainty, which forces surgeries to be scheduled close together to avoid costly OR idle time; the last surgery is scheduled earlier than NORA Model Option 2 for all three settings of weights, which results from the attempts to reduce the possibility of OR overtime.

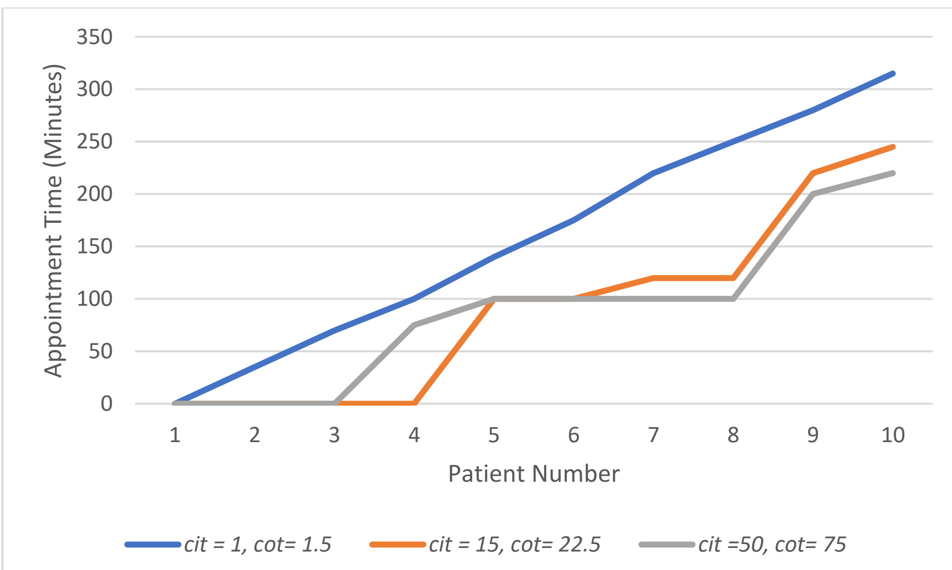

Figure 15. OR schedule for NORA Model Option 2 STD1

Figure 16 shows the best OR schedule for NORA Model Option 2 STD2. For c_{it} = 1, c_{ot}= 1.5, patients are scheduled to arrive separately with an interval close to their mean surgery duration. For c_{it} = 15, c_{ot}= 22.5 and c_{it} = 50, c_{ot}= 75, most patients are scheduled to arrive in groups, while the last surgery is scheduled earlier. Similar to the schedule above, surgeries tend to be scheduled close to avoid potential OR idle time; the last surgery is surgery is scheduled even earlier due to higher uncertainty for the model with a standard deviation of 20 minutes.

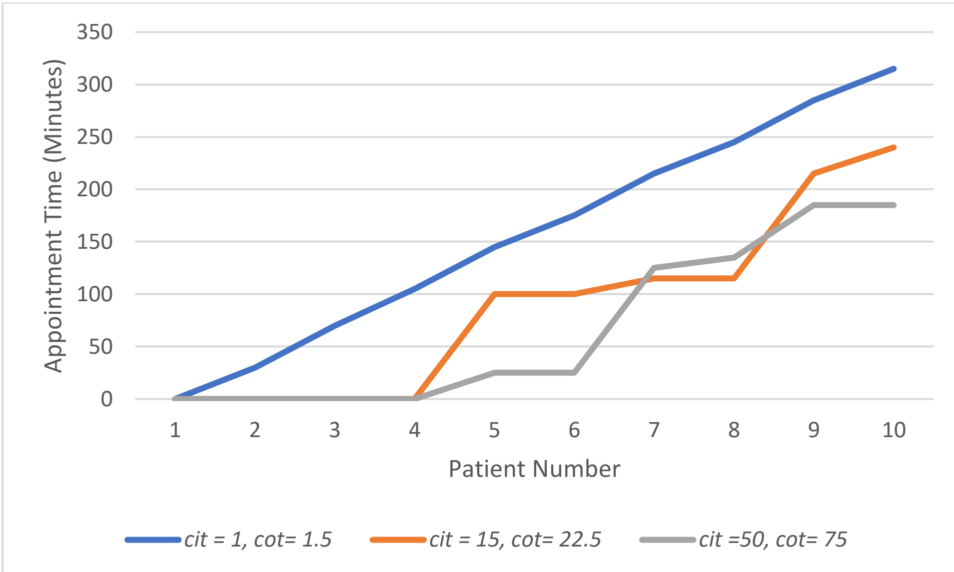

Figure 16. OR schedule for NORA Model Option 2 STD2

4.3.3 NORA Model Option 3 With Larger Standard Deviation: Thirteen Surgery Appointments in a 420 Minute Session

The NORA model scheduling 13 surgeries within 420 minutes will also be tested. The results are displayed in Table 10. For standard deviation = 15 minutes (NORA Model Option 3 STD1), under the condition of c_{it} = 1, c_{ot}= 1.5, mean total waiting time, total idle time and overtime are 155.11±10.98, 61.09±2.28 and 49.43±1.87 minutes when expected total costs are lowest. Average waiting time for each patient is 11.93 minutes. OR idle time is 11.66 minutes longer than OR overtime. Under the condition of c_{it} = 15, c_{ot}= 22.5, mean total waiting times, total idle time and overtime are 706.02±21.08, 10.63±1.18 and 16.49±1.85 minutes when expected total costs are lowest. Average waiting time for each patient will be 54.31 minutes. Patient waiting time increases

355.17% while OR idle time and overtime decrease 82.60% and 66.64%. Under the condition of c_{it} = 50, c_{ot}= 75, mean total waiting times, total idle time and overtime are 746.93±15.31, 2.29±0.36 and 10.24±1.20 minutes when expected total costs are lowest. Average waiting time for each patient increases to 57.46 minutes. Patient waiting time increases 29.20%% while OR idle time and overtime decrease 80.15% and 2.43%. The results show that larger standard deviation still has a negative impact on OR performance in a NORA policy setting with more surgeries to perform.

Table 10. Results for NORA Model Option 3 with standard deviation of 15 minutes (STD1) and 20 minutes (STD2)

Performance Measures		NORA Model Option 3	NORA Model Option 3 STD1	NORA Model Option 3 STD2
c_{it}=1, c_{ot}=1.5	Total Waiting Time	102.64±6.04	155.11±10.98	230.19±16.86
	Total Idle Time	54.94±1.78	61.09±2.28	71.13±2.75
	Overtime	43.65±1.17	49.43±1.87	59.11±2.76
	Utilization	0.88±0.00	0.87±0.01	0.85±0.00
	WTITOT1.5	223.05±6.18	290.36±11.70	389.98±18.37
c_{it}=15, c_{ot}=22.5 (Percentage compared to c_{it} = 1, c_{ot}= 1.5)	Total Waiting Time	697.33±11.75 (+579.39%)	706.02±21.08 (+355.17%)	827.69±26.49 (+259.57%)
	Total Idle Time	12.53±0.93 (-77.19%)	10.63±1.18 (-82.60%)	17.85±1.62 (-74.91%)
	Overtime	12.79±1.27 (-70.70%)	16.49±1.85 (-66.64%)	24.45±2.65 (-58.64%)
	Utilization	0.96±0.00 (+9.09%)	0.97±0.00 (+11.49%)	0.95±0.00 (+11.76%)
	WTIT15OT22.5	1268.86±45.07 (+468.87%)	1236.36±54.05 (+325.80%)	1645.61±74.22 (+321.97%)
c_{it}=50, c_{ot}=75 (Percentage compared to c_{it} = 15, c_{ot}= 22.5)	Total Waiting Time	746.93±15.31 (+7.11%)	912.21±23.04 (+29.20%)	1023.84±30.43 (+23.70%)
	Total Idle Time	2.29±0.36 (-81.72%)	2.11±0.49 (-80.15%)	2.34±0.50 (-86.89%)
	Overtime	10.24±1.20 (-19.94%)	16.09±1.85 (-2.43%)	22.85±2.61 (-6.54%)
	Utilization	0.99±0.00 (+3.13%)	0.99±0.00 (+2.06%)	0.99±0.00 (+4.21%)
	WTIT50OT75	1629.69±98.73 (+28.44%)	2224.63±152.95 (+79.93%)	2854.11±215.54 (+73.44%)

For standard deviation = 20 minutes (NORA Model Option 3 STD2), under the condition of c_{it} = 1, c_{ot}= 1.5, mean total waiting times, total idle time and overtime are 230.19±16.86, 71.13±2.75 and 59.11±2.76 minutes when expected total costs are lowest. Average waiting time for each patient is 17.71 minutes. OR idle time is 12.02 minutes longer than OR overtime. Under the condition of c_{it} = 15, c_{ot}= 22.5, mean total waiting times, total idle time and overtime are 827.69±26.49, 17.85±1.62 and 24.45±2.65 minutes when expected total costs are lowest. Average waiting time for each patient will be 63.67 minutes. Patient waiting time increases 259.57% while OR idle time and overtime decrease 74.91% and 58.64%. Under the condition of c_{it} = 50, c_{ot}= 75, mean total waiting times, total idle time and overtime are 1023.84±30.43, 2.34±0.50 and 22.85±2.61 minutes when expected total costs are lowest. Average waiting time for each patient increases to 78.76 minutes Patient waiting time increases 23.70% while OR idle time and overtime decrease 86.89% and 6.54%. Same as NORA model with same number of surgery appointments, longer standard deviation still has a negative impact on NORA model with same session length regarding overall OR performance.

Figure 17 shows the best OR schedules for the NORA Model Option 3 STD1. For c_{it} = 1, c_{ot}= 1.5, patients are scheduled to arrive separately with an interval close to their mean surgery duration. For c_{it} = 15, c_{ot}= 22.5 and c_{it} = 50, c_{ot}= 75, patients are scheduled to arrive in groups of two or three, while the last surgery is scheduled 70 and 125 minutes earlier. Larger standard deviation causes higher uncertainty, which forces more surgeries to be scheduled close together to avoid costly OR idle time.

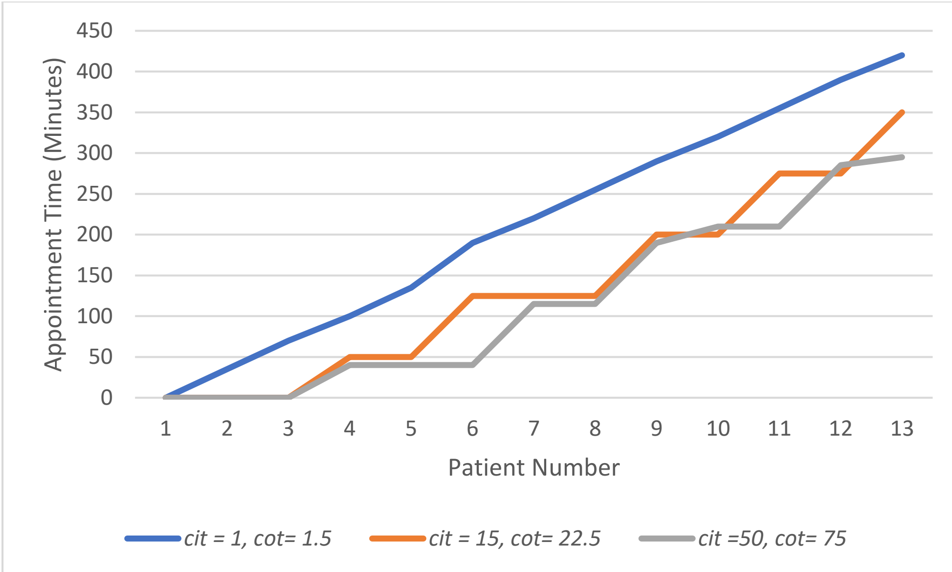

Figure 17. OR schedule for NORA Model Option 3 STD1

Figure 18 shows the best OR schedule for the NORA model of 420 minutes session length with a standard deviation of 20 minutes. For c_{it} = 1, c_{ot}= 1.5, patients are scheduled to arrive separately with an interval close to their mean surgery duration. For c_{it} = 15, c_{ot}= 22.5, first five patients are scheduled to arrive at same time. For c_{it} = 50, c_{ot}= 75, patients are scheduled to arrive in groups of two or three, while the last surgery is scheduled 170 minutes earlier than c_{it} = 1, c_{ot}= 1.5. Similar to the schedule above, the main difference for this schedule from NORA Model Option 3 is that more surgeries are scheduled close together to keep OR running.

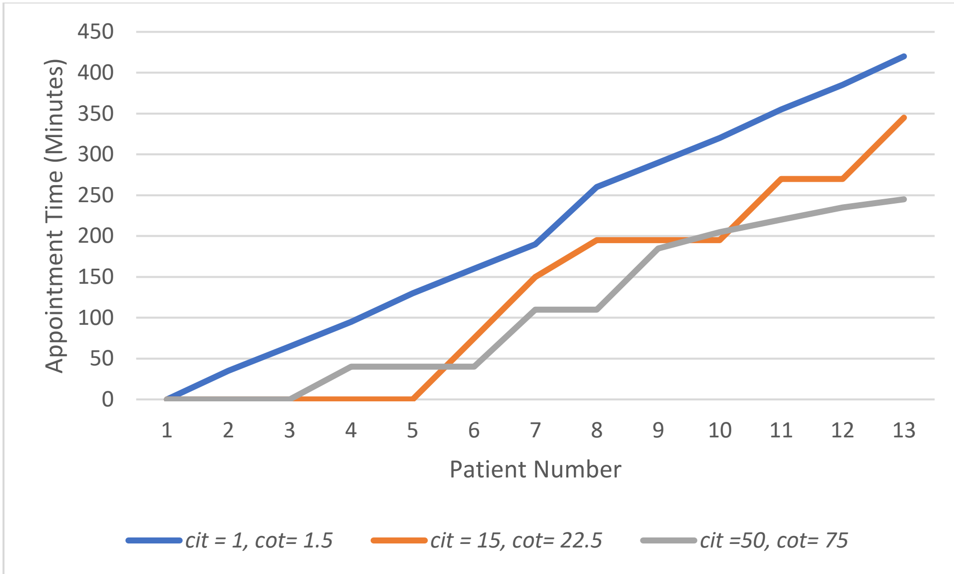

Figure 18. OR schedule for NORA Model Option 3 STD2

4.3.4 Comparison of Basic Model and NORA Model for Different Standard Deviations

Table 11 shows the key results for the Basic Model and the NORA Models with standard deviation = 15 minutes. Comparing the Basic Model STD1 and the NORA Model Option 2 STD1, for all three settings of c_{it} and c_{ot}, patient waiting time is lower while OR idle time and overtime are slightly higher for NORA model with same number of surgery appointments. ANOVA results (See Appendix Table A6-A8) show that there are no significant differences for performance measure of expected total costs, which means NORA policy can improve OR efficiency without significantly increasing expected total costs.

Comparing the Basic Model STD1 and the NORA Model Option 3 STD1, for the settings of c_{it}=1, c_{ot}=1.5, patient waiting time, OR idle time and overtime are all longer for NORA model Option 3 STD1. ANOVA results (See Appendix Table A6) show that there is a significant increase for performance measure of expected total costs. For the setting of c_{it}=15, c_{ot}=22.5, patient waiting time and OR idle time are longer while OR overtime is shorter for NORA model. According to

ANOVA results (See Appendix Table A7), there is no significant defference for performance measure of expected total costs. For the setting of c_{it}=50, c_{ot}=75, patient waiting time is longer while OR idle time and overtime are shorter for NORA model. ANOVA results (See Appendix Table A8) indicate that there is no significant difference for performance measure of expected total costs. Though there are significant increases for NORA Model Option 3 STD1 when c_{it} and c_{ot} are lower, this model accommodates three more surgeries in the same session length. Therefore, NORA is better overall in terms of expected total costs than the Basic Model even when there is more variability in surgery duration especially when weights of coefficients for OR idle time and overtime are high.

Table 11. Comparison of results for Basic Model and NORA Models with Standard Deviation =15 minutes

Performance Measures		Basic Model STD1	NORA Model Option 2 STD1	NORA Model Option 3 STD1
c_{it}=1, c_{ot}=1.5	Total Waiting Time	119.61±8.96	102.07±7.73	155.11±10.98
	Total Idle Time	46.08±1.89	48.70±1.90	61.09±2.28
	Overtime	45.29±1.85	47.70±1.77	49.43±1.87
	Utilization	0.90±0.00	0.86±0.01	0.87±0.01
	WTITOT1.5	233.62±9.89	222.32±8.61	290.36±11.70
c_{it}=15, c_{ot}=22.5	Total Waiting Time	574.65±15.34	524.65±14.22	706.02±21.08
	Total Idle Time	6.62±0.76	6.62±0.81	10.63±1.18
	Overtime	19.82±1.89	18.63±1.85	16.49±1.85
	Utilization	0.98±0.00	0.98±0.00	0.97±0.00
	WTIT15OT22.5	1119.72±52.26	1043.26±49.72	1236.36±54.05
c_{it}=50, c_{ot}=75	Total Waiting Time	624.22±17.28	536.53±14.31	912.21±23.04
	Total Idle Time	2.33±0.49	3.99±0.52	2.11±0.49
	Overtime	18.75±1.89	18.80±1.86	16.09±1.85
	Utilization	0.99±0.00	0.99±0.00	0.99±0.00
	WTIT50OT75	2147.15±151.12	2146.23±146.02	2224.63±152.95

Table 12 shows the key results for the Basic Model and the NORA Models with standard deviation = 20 minutes. Comparing the Basic Model STD2 and the NORA Model Option 3 STD2, for the settings of c_{it}=1, c_{ot}=1.5, OR idle time and overtime are longer while patient waiting time is shorter for NORA model. ANOVA results (See Appendix Table A10) show that there is no significant difference for performance measure of expected total costs. For the setting of c_{it}=15, c_{ot}=22.5, OR idle time is longer while patient waiting time and OR overtime is shorter for NORA model. According to ANOVA results (See Appendix Table A11), there is no significant difference for performance measure of expected total costs, which means NORA policy can perform same number of surgeries within shorter session length without significantly increase expected total costs. For the setting of c_{it}=50, c_{ot}=75, patient waiting time is longer while OR idle time and overtime are shorter for NORA model. ANOVA results (See Appendix Table A12) indicate that there is also no significant difference on expected total cost. Therefore, NORA Model outperforms Basic Model in a way where it schedules same number of surgeries with 105 minutes shorter session length when expected total costs are not significantly different.

Table 12. Comparison of results for Basic Model and NORA Models with Standard Deviation =20 minutes

Performance Measures		Basic Model STD2	NORA Model Option 2 STD1	NORA Model Option 2 STD2
c_{it}=1, c_{ot}=1.5	Total Waiting Time	174.97±12.96	149.28±11.71	230.19±16.86
	Total Idle Time	53.17±2.36	57.18±2.29	71.13±2.75
	Overtime	52.11±2.58	55.91±2.57	59.11±2.76
	Utilization	0.88±0.01	0.84±0.01	0.85±0.00
	WTITOT1.5	306.31±14.45	290.33±13.34	389.98±18.37
c_{it}=15, c_{ot}=22.5	Total Waiting Time	602.37±29.72	558.13±18.54	827.69±26.49
	Total Idle Time	9.30±1.03	10.53±1.12	17.85±1.62
	Overtime	25.43±2.58	25.12±2.56	24.45±2.65
	Utilization	0.98±0.00	0.96±0.00	0.95±0.00
	WTIT15OT22.5	1313.91±70.43	1281.40±67.98	1645.61±74.22
c_{it}=50, c_{ot}=75	Total Waiting Time	681.21±22.40	732.52±20.33	1023.84±30.43
	Total Idle Time	3.08±0.46	2.38±0.49	2.34±0.50
	Overtime	24.86±2.58	24.07±2.55	22.85±2.61
	Utilization	0.99±0.00	0.99±0.00	0.99±0.00
	WTIT50OT75	2699.82±206.58	2656.28±203.04	2854.11±215.54

Comparing the Basic Model STD2 and the NORA Model Option 3 STD2, for the settings of c_{it}=1, c_{ot}=1.5, patient waiting time, OR idle time and overtime are all longer for NORA model. ANOVA results (See Appendix Table A10) show that there is a significant increase for performance measure of expected total costs. For the setting of c_{it}=15, c_{ot}=22.5, patient waiting time and OR idle time are longer while OR overtime is shorter for NORA model. According to ANOVA results (See Appendix Table A11), there is a significant increase for performance measure of expected total costs. For the setting of c_{it}=50, c_{ot}=75, patient waiting time is longer while OR idle time and overtime are shorter for NORA model. ANOVA results (See Appendix Table A12) indicate that there is no significant difference in expected total costs.

Overall, the NORA Model Option 2 performs better than the Basic Model in terms of OR performance. Option 3 results in a higher expected total cost. However, in this case, more surgeries are performed in the same session length when compared to the Basic Model. Therefore, NORA model is still better overall in terms of expected total costs especially when OR idle time and overtime have higher weights of coefficients.

4.4 Experiments with Variation in Mean Surgery Duration

Different types of surgeries typically have different mean durations. This experiment aims at figuring out how NORA policy can perform to improve OR efficiency when the mean time to complete the surgery is diverse. The original experiments in Section 4.1 used a mean surgery duration of 42 minutes. In this section, we analyze the impact of different mean surgery durations. We assume that the durations of NORA stage stay the same following the distribution of LOGN (10.5, 3.5) and mean durations of 25 minutes, 50 minutes and 75 minutes. The same standard deviation of 14 minutes is used for each case. Thus, there is relatively more variability in the surgery duration for shorter mean values than longer mean values. In each case, the session length is adjusted to accommodate the scheduling of ten surgery appointments. Results for the Basic Model and Options 2 and 3 for the NORA Model are presented in Sections 4.4.1-4.4.3. An overall comparison across the different models is provided in Section 4.4.4.

4.4.1 Basic Model with Different Mean Durations

The Basic Model schedules ten surgeries in a session length of 355 minutes $= (25 + 10.5)\ minutes \times 10$ for a mean duration of 25 minutes, 605 minutes $= (50 + 10.5)\ minutes \times 10$ for a mean duration of 50 minutes and 855 minutes$= (75 + 10.5)\ minutes \times 10$ for a mean duration of 75 minutes. The results are provided in Table 13. For mean duration = 25 minutes (Basic Model Mean1), when c_{it} = 1, c_{ot}= 1.5, mean total waiting times, total idle time and overtime are 49.70±3.37, 44.36±1.32 and 44.01±0.91 minutes when expected total costs are lowest. Average waiting time for each patient is 4.97 minutes. Under the condition of c_{it} = 15, c_{ot}= 22.5, mean total waiting times, total idle time and overtime are 249.72±9.13, 6.22±0.50 and 12.78±1.12 minutes when expected total costs are lowest. Average waiting time for each patient will be 24.97 minutes. Waiting time for patients has increased 402.45% while OR idle time and overtime have decreased 85.98% and 70.96%. When c_{it} = 50, c_{ot}= 75, mean total waiting times, total idle time and overtime are 486.80±9.84, 2.12±0.34 and 11.18±1.07 minutes when expected total costs are lowest. Average waiting time for each patient increases to 48.68 minutes. Patient waiting time is 94.94% longer while OR overtime and idle time are 65.92% and 12.52% lower.

For mean duration = 50 minutes (Basic Model Mean2), when c_{it} = 1, c_{ot}= 1.5, mean total waiting times, total idle time and overtime are 162.11±10.27, 39.30±1.97 and 39.13±2.11 minutes when expected total costs are lowest. Average waiting time for each patient is 16.21 minutes.

Under the condition of c_{it} = 15, c_{ot}= 22.5, mean total waiting times, total idle time and overtime are 494.61±15.92, 10.94±1.18 and 21.92±2.02 minutes when expected total costs are lowest. Average waiting time for each patient will be 49.46 minutes. Patient waiting time for patients has increased 205.11% while OR idle time and overtime have decreased 72.16% and 43.98%. When c_{it} = 50, c_{ot}= 75, mean total waiting times, total idle time and overtime are 911.81±18.35, 1.46±0.33 and 20.89±2.02 minutes when expected total costs are lowest. Average waiting time for each patient increases to 91.18 minutes. Patient waiting time increases 84.35% while OR idle time and overtime decrease 86.65% and 4.70%. With the increase of mean durations, average expected total costs also have an increasing tendency. Patient waiting time is the measure that changes the most.

For mean duration = 75 minutes (Basic Model Mean3), when c_{it} = 1, c_{ot}= 1.5, mean total waiting times, total idle time and overtime are 175.37±12.04, 82.78±3.32 and 81.31±2.90 minutes when expected total costs are lowest. Average waiting time for each patient is 17.54 minutes. Under the condition of c_{it} = 15, c_{ot}= 22.5, mean total waiting times, total idle time and overtime are 600.66±24.03, 11.08±1.12 and 33.44±3.06 minutes when expected total costs are lowest. Average waiting time for each patient will be 60.07 minutes. Patient waiting time for patients has increased 242.51% while OR idle time and overtime have decreased 86.62% and 58.87%. When c_{it} = 50, c_{ot}= 75, mean total waiting times, total idle time and overtime are 807.28±26.83, 2.82±0.59 and 31.08±3.01 minutes when expected total costs are lowest. Average waiting time for each patient increases to 80.73 minutes. Patient waiting time increases 34.40% while OR idle time and overtime decrease 74.55% and 7.06%. Patient waiting time, OR idle time and overtime all have the tendencies to increase as the mean duration increases.

Table 13. Results for Basic Model with mean durations of 25 (Mean1), 50 (Mean2) and 75 (Mean3) minutes

Performance Measures		Basic Model Mean1	Basic Model Mean2	Basic Model Mean3
c_{it}=1, c_{ot}=1.5	Total Waiting Time	49.70±3.37	162.11±10.27	175.37±12.04
	Total Idle Time	44.36±1.32	39.30±1.97	82.78±3.32
	Overtime	44.01±0.91	39.13±2.11	81.31±2.90
	Utilization	0.89±0.00	0.94±0.00	0.91±0.00
	WTITOT1.5	160.08±3.70	260.11±11.56	380.12±13.46
c_{it}=15, c_{ot}=22.5 (Percentage compared to c_{it} = 1, c_{ot}= 1.5)	Total Waiting Time	249.72±9.13 (+402.45%)	494.61±15.92 (+205.11%)	600.66±24.03 (+242.51%)
	Total Idle Time	6.22±0.50 (-85.98%)	10.94±1.18 (-72.16%)	11.08±1.12 (-86.62%)
	Overtime	12.78±1.12 (-70.96%)	21.92±2.02 (-43.98%)	33.44±3.06 (-58.87%)
	Utilization	0.98±0.00 (+10.11%)	0.98±0.00 (+4.26%)	0.99±0.00 (+8.79%)
	WTIT15OT22.5	630.72±31.09 (+294.00%)	1151.77±53.63 (+342.80%)	1519.09±84.64 (+299.63%)
c_{it}=50, c_{ot}=75 (Percentage compared to c_{it} = 15, c_{ot}=22.5)	Total Waiting Time	486.80±9.84 (+94.94%)	911.81±18.35 (+84.35%)	807.28±26.83 (+34.40%)
	Total Idle Time	2.12±0.34 (-65.92%)	1.46±0.33 (-86.65%)	2.82±0.59 (-74.55%)
	Overtime	11.18±1.07 (-12.52%)	20.89±2.02 (-4.70%)	31.08±3.01 (-7.06%)
	Utilization	0.99±0.00 (+1.02%)	0.99±0.00 (+1.02%)	0.99±0.00 (+0.00%)
	WTIT50OT75	1430.99±85.06 (+126.88%)	2551.33±163.25 (+121.51%)	3278.81±241.81 (+115.84%)

Figure 19 shows the best OR schedule for the Basic Model Mean1. For c_{it} = 1, c_{ot}= 1.5 and c_{it} = 15, c_{ot}= 22.5, patients are scheduled to arrive separately with an interval close to their mean surgery duration. For c_{it} = 50, c_{ot}= 75, patients are scheduled to arrive in groups of two or three, while the last surgery is scheduled similar to the setting of c_{it} = 15, c_{ot}= 22.5. Scheduling surgeries close together can potentially avoid costly OR idle time and overtime.

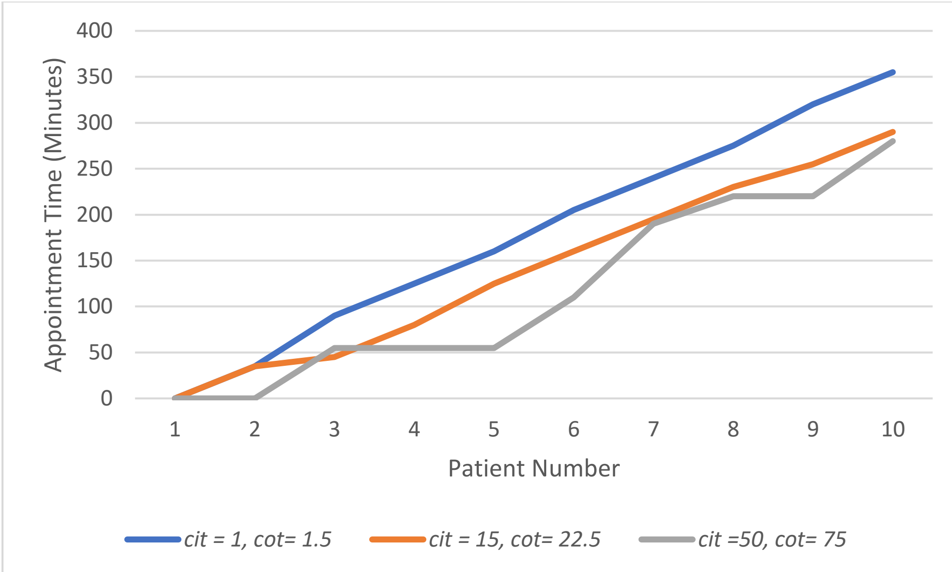

Figure 19. OR Schedule for Basic Model Mean1

Figure 20 shows the best OR schedule for the Basic Model Mean2. For c_{it} = 1, c_{ot}= 1.5 and c_{it} = 15, c_{ot}= 22.5, patients are scheduled to arrive separately with an interval close to their mean surgery duration. For c_{it} = 50, c_{ot}= 75, patients are scheduled to arrive in groups of two or three. Compared to the schedule in Figure 17, fewer surgeries are scheduled in a group. This is because with the longer mean durations, there is more room to schedule surgeries and there is less variability in surgery durations.

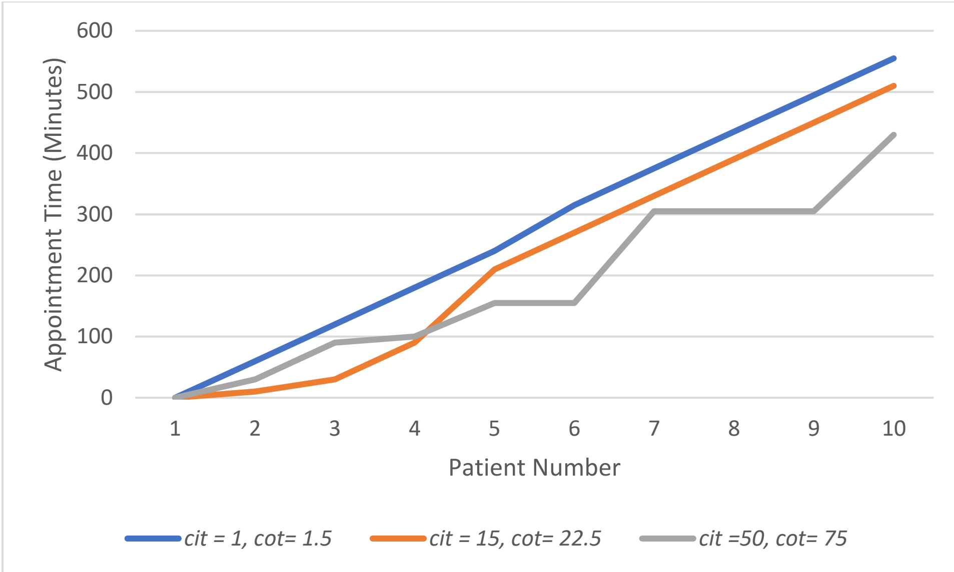

Figure 20. OR Schedule for Basic Model Mean2

Figure 21 shows the best OR schedule for the Basic Model Mean3. For all three settings, patients are scheduled to arrive separately with an interval close to their mean surgery duration, while scheduled time of last surgery is slightly different. This schedule shows the same tendency as Figure 18, as longer mean duration and relatively less variability in duration allow more room to schedule surgeries for the consideration of OR idle time and overtime.

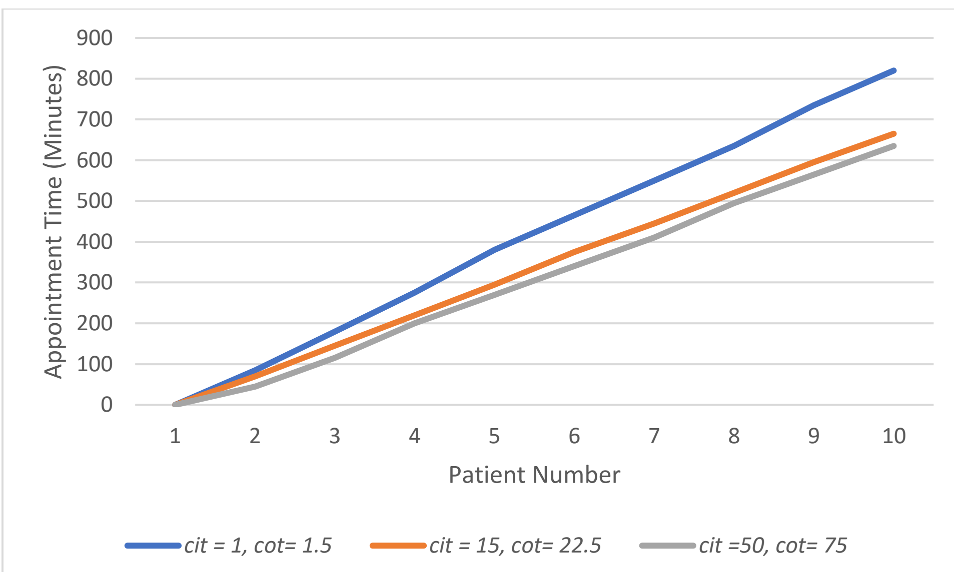

Figure 21. OR Schedule for Basic Model Mean3

4.4.2 NORA Model Option 2 with Different Mean Durations: Ten Surgery Appointments

NORA model of same number of surgery appointments will use ten surgeries following session length of 250, 500 and 750 minutes. The results are provided in Table 14. For mean duration = 25 minutes (NORA Model Option 2 Mean1), when c_{it} = 1, c_{ot}= 1.5, mean total waiting times, total idle time and overtime are 54.06±3.80, 29.25±1.17 and 28.69±0.89 minutes when expected total costs are lowest. Average waiting time for each patient is 5.41 minutes. Under the condition of c_{it} = 15, c_{ot}= 22.5, mean total waiting times, total idle time and overtime are 224.39±7.43, 3.92±0.44 and 10.81±0.99 minutes when expected total costs are lowest. Average waiting time for each patient will be 22.44 minutes. Waiting time for patients has increased 315.08% while OR idle time and overtime have decreased 86.60% and 62.32%. When c_{it} = 50, c_{ot}= 75, mean total waiting times, total idle time and overtime are 324.38±8.38, 0.86±0.19 and 10.18±0.99 minutes when expected total costs are lowest. Average waiting time for each patient increases to 32.44 minutes. Patient waiting time is 44.56% longer while OR idle time is 78.06% lower. The results show that NORA model outperforms Basic Model Mean1 in patient waiting time, OR idle time and overtime.

For mean duration = 50 minutes (NORA Model Option 2 Mean2), under the condition of c_{it} = 1, c_{ot}= 1.5, mean total waiting times, total idle time and overtime are 140.86±9.11, 44.06±2.07 and 43.06±2.00 minutes when expected total costs are lowest. Average waiting time for each patient is 14.09 minutes. Patient waiting time is still short. Under the condition of c_{it} = 15, c_{ot}= 22.5, mean total waiting times, total idle time and overtime are 606.28±16.19, 5.64±0.82 and 20.52±1.98 minutes when expected total costs are lowest. Average waiting time for each patient will be 60.63 minutes. Patient waiting time for patients increases 330.41% while OR idle time and overtime decrease 87.20% and 52.35%. Under the condition of c_{it} = 50, c_{ot}= 75, mean total waiting times, total idle time and overtime are 597.22±16.46, 3.34±0.59 and 20.39±1.98 minutes when expected total costs are lowest. Average waiting time for each patient increases to 59.72 minutes. OR idle time and overtime decrease 40.78% and 0.63%. The results show that this model still outperforms Basic Model Mean2, but the gaps are much closer.

Table 14. Results for NORA Model Option 2 with mean durations of 25 (Mean1), 50 (Mean2) and 75 (Mean3) minutes

Performance Measures		NORA Model Option 2 Mean1	NORA Model Option 2 Mean2	NORA Model Option 2 Mean3
c_{it}=1, c_{ot}=1.5	Total Waiting Time	54.06±3.80	140.86±9.11	199.03±12.70
	Total Idle Time	29.25±1.17	44.06±2.07	71.96±3.18
	Overtime	28.69±0.89	43.06±2.00	70.35±3.01
	Utilization	0.89±0.00	0.92±0.00	0.91±0.00
	WTITOT1.5	126.35±4.03	249.51±10.10	376.51±14.25
c_{it}=15, c_{ot}=22.5 (Percentage compared to c_{it} = 1, c_{ot}= 1.5)	Total Waiting Time	224.39±7.43 (+315.08%)	606.28±16.19 (+330.41%)	660.38±21.83 (+231.80%)
	Total Idle Time	3.92±0.44 (-86.60%)	5.64±0.82 (-87.20%)	14.65±141 (-79.64%)
	Overtime	10.81±0.99 (-62.32%)	20.52±1.98 (-52.35%)	33.28±3.03 (-52.69%)
	Utilization	0.98±0.00 (+10.11%)	0.99±0.00 (+7.61%)	0.98±0.00 (+7.69%)
	WTIT15OT22.5	526.34±26.81 (+316.57%)	1152.56±54.54 (+361.93%)	1628.98±80.33 (+332.65%)
c_{it}=50, c_{ot}=75 (Percentage compared to c_{it} = 15, c_{ot}=22.5)	Total Waiting Time	324.38±8.38 (+44.56%)	597.22±16.46 (-1.49%)	901.54±25.33 (+36.52%)
	Total Idle Time	0.86±0.19 (-78.06%)	3.34±0.59 (-40.78%)	2.99±0.65 (-79.59%)
	Overtime	10.18±0.99 (-5.83%)	20.39±1.98 (-0.63%)	30.59±2.99 (-8.08%)
	Utilization	0.99±0.00 (+1.02%)	0.99±0.00 (+0.00%)	0.99±0.00 (+1.02%)
	WTIT50OT75	1130.57±79.35 (+114.80%)	2293.15±156.52 (+98.96%)	3344.87±238.49 (+105.34%)

For mean duration = 75 minutes (NORA Model Option 2 Mean3), under the condition of c_{it} = 1, c_{ot}= 1.5, mean total waiting times, total idle time and overtime are 199.03±12.70, 71.96±3.18 and 70.35±3.01 minutes when expected total costs are lowest. Average waiting time for each patient is 19.90 minutes. Under the condition of c_{it} = 15, c_{ot}= 22.5, mean total waiting times, total idle time and overtime are 660.38±21.83, 14.65±141 and 33.28±3.03 minutes when expected total costs are lowest. Average waiting time for each patient will be 66.04 minutes. Patient waiting time for patients increases 231.80% while OR idle time and overtime decreases 79.64% and 52.69%. Under the condition of c_{it} = 50, c_{ot}= 75, mean total waiting times, total idle time and overtime are 901.54±25.33, 2.99±0.65 and 30.59±2.99 minutes when expected total costs are lowest. Average waiting time for each patient increases to 90.15 minutes. Patient waiting time increases 231.80% while OR idle time and overtime decrease79.59% and 8.08%. When the weights of OR idle time and overtime are higher, Basic Model Mean3 has a better performance on average expected total costs with a longer session length.

Figure 22 shows the best OR schedule for NORA Model Option 2 Mean1. For c_{it} = 1, c_{ot}= 1.5, patients are scheduled to arrive separately with an interval close to their mean surgery duration. For c_{it} = 15, c_{ot}= 22.5 and c_{it} = 50, c_{ot}= 75, first two patients are scheduled to arrive in a group, while the last surgery is scheduled earlier than the setting of c_{it} = 1, c_{ot}= 1.5. The schedule differs from Basic Model Mean1 when c_{it} and c_{ot} have higher values. There are fewer surgeries scheduled close together in NORA Model Option 2 Mean1.

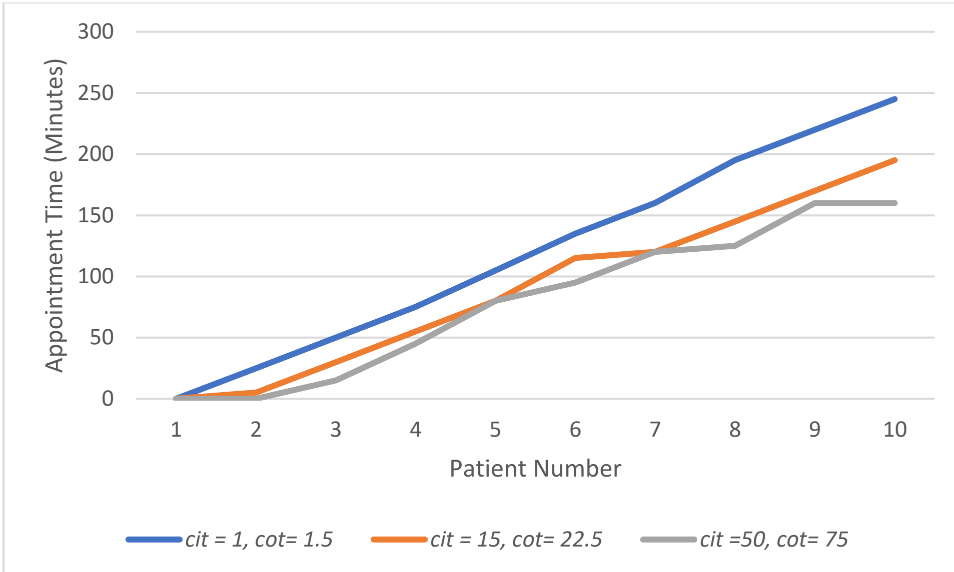

Figure 22. OR Schedule for NORA Model Option 2 Mean1

Figure 23 shows the best OR schedule for NORA Model Option 2 Mean2. For c_{it} = 1, c_{ot}= 1.5, patients are scheduled to arrive separately with an interval close to their mean surgery duration. For c_{it} = 15, c_{ot}= 22.5 and c_{it} = 50, c_{ot}= 75, first few patients and patients in the middle are scheduled to arrive in a group. Similar to the results above, there are fewer surgeries scheduled close together than Basic Model Mean2.

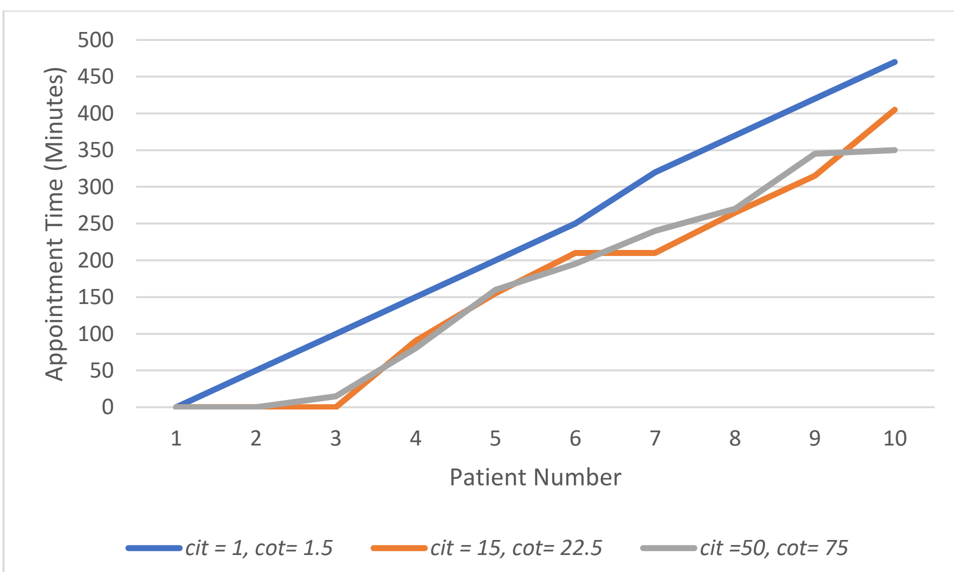

Figure 23. OR Schedule for NORA Model Option 2 Mean2

Figure 24 shows best the OR schedule for NORA Model Option 2 Mean3. For c_{it} = 1, c_{ot}= 1.5, patients are scheduled to arrive separately with an interval close to their mean surgery duration. For c_{it} = 15, c_{ot}= 22.5 and c_{it} = 50, c_{ot}= 75, patients are scheduled to arrive in a group or with a small interval in between. The Last surgery is scheduled 50 and 100 minutes ahead of the setting of c_{it} = 1, c_{ot}= 1.5. The schedule differs from Basic Model Mean3, where this model has more surgeries to be scheduled in groups.

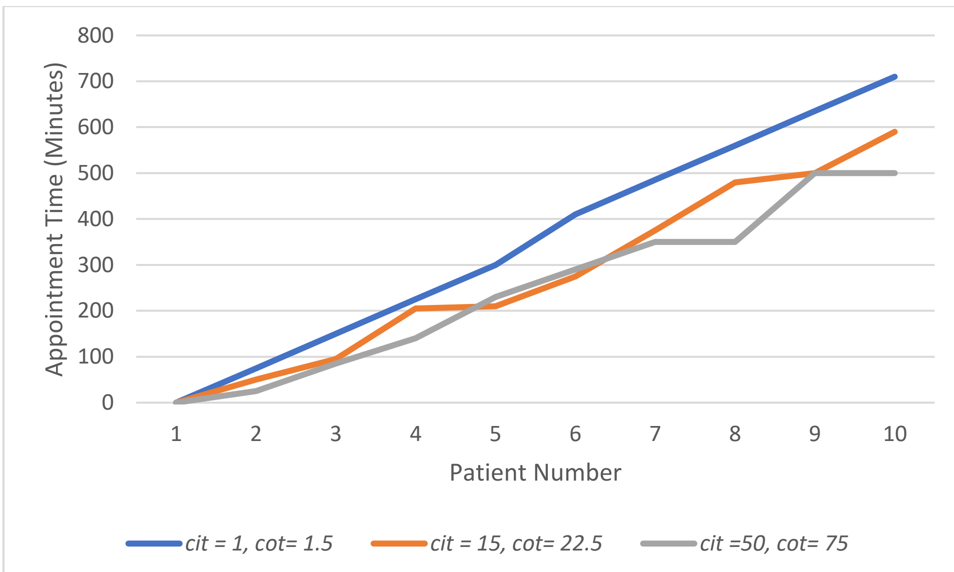

Figure 24. OR Schedule for NORA Model Option 2 Mean3

4.4.3 NORA Model Option 3 with Different Mean Durations: Same Session Length with more Surgery Appointments

The impact of a NORA policy is being able to schedule more surgeries per session. NORA model of same session length will follow the session length of 355, 605 and 855 minutes. The maximum allowed surgeries numbers for these session lengths are 14, 12 and 11. The results are provided in Table 15. For mean duration = 25 minutes (NORA Model Option 3 Mean1), when c_{it} = 1, c_{ot}= 1.5, mean total waiting times, total idle time and overtime are 107.67±6.28, 33.92±1.32 and 28.38±1.07

minutes when expected total costs are lowest. Average waiting time for each patient is 7.69 minutes. Under the condition of c_{it} = 15, c_{ot}= 22.5, mean total waiting times, total idle time and overtime are 296.27±11.62, 7.46±0.72 and 10.37±1.05 minutes when expected total costs are lowest. Average waiting time for each patient will be 21.16 minutes. Waiting time for patients increases 175.16% while OR idle time and overtime decreases 78.01% and 63.46%. When c_{it} = 50, c_{ot}= 75, mean total waiting times, total idle time and overtime are 505.02±13.45, 2.49±0.37 and 9.69±1.03 minutes when expected total costs are lowest. Average waiting time for each patient increases to 36.07 minutes. Patient waiting time is 70.46% longer while OR overtime and idle time are 66.62% and 6.56% lower. The results have slightly higher expected total costs than Basic Model Mean1, which is an allowable tolerance since four more surgeries are scheduled.

For mean duration = 50 minutes (NORA Model Option 3 Mean2), when c_{it} = 1, c_{ot}= 1.5, mean total waiting times, total idle time and overtime are 140.74±8.59, 80.69±2.48 and 74.73±2.06 minutes when expected total costs are lowest. Average waiting time for each patient is 11.73 minutes. Under the condition of c_{it} = 15, c_{ot}= 22.5, mean total waiting times, total idle time and overtime are 606.50±20.00, 9.36±1.11 and 20.74±2.08 minutes when expected total costs are lowest with. Average waiting time for each patient will be 50.54 minutes. Patient waiting time for patients increases 330.94% while OR idle time and overtime decrease 88.40% and 72.25%. When c_{it} = 50, c_{ot}= 75, mean total waiting times, total idle time and overtime are 879.01±21.83, 3.37±0.63 and 20.16±2.07 minutes when expected total costs are lowest. Average waiting time for each patient increases to 73.25 minutes. Patient waiting time increases 44.93% while OR idle time and overtime decrease 64.00% and 2.80%. Similar to the results above, since there are 2 more surgeries to be scheduled in this model, the slightly higher expected total costs should be an allowable tolerance compared to Basic Model Mean2.

Table 15. Results for NORA Model Option 3 with mean durations of 25 (Mean1), 50 (Mean2) and 75 (Mean3) minutes

Performance Measures		NORA Model Option 3 Mean1	NORA Model Option 3 Mean2	NORA Model Option 3 Mean3
c_{it}=1, c_{ot}=1.5	Total Waiting Time	107.67±6.28	140.74±8.59	243.02±15.11
	Total Idle Time	33.92±1.32	80.69±2.48	74.15±3.32
	Overtime	28.38±1.07	74.73±2.06	42.15±2.98
	Utilization	0.91±0.00	0.88±0.00	0.92±0.00
	WTITOT1.5	184.15±6.73	333.52±9.84	384.90±16.49
c_{it}=15, c_{ot}=22.5 (Percentage compared to c_{it} = 1, c_{ot}= 1.5)	Total Waiting Time	296.27±11.62 (+175.16%)	606.50±20.00 (+330.94%)	792.64±25.60 (+226.16%)
	Total Idle Time	7.46±0.72 (-78.01%)	9.36±1.11 (-88.40%)	14.50±1.57 (-80.45%)
	Overtime	10.37±1.05 (-63.46%)	20.74±2.08 (-72.25%)	21.07±2.58 (-50.01%)
	Utilization	0.97±0.00 (+6.59%)	0.98±0.00 (+11.36%)	0.98±0.00 (+6.52%)
	WTIT15OT22.5	641.36±30.20 (+248.28%)	1213.57±58.72 (+263.87%)	1484.34±72.90 (+285.64%)
c_{it}=50, c_{ot}=75 (Percentage compared to c_{it} = 15, c_{ot}=22.5)	Total Waiting Time	505.02±13.45 (+70.46%)	879.01±21.83 (+44.93%)	1098.18±29.24 (+38.55%)
	Total Idle Time	2.49±0.37 (-66.62%)	3.37±0.63 (-64.00%)	3.98±0.80 (-72.55%)
	Overtime	9.69±1.03 (-6.56%)	20.16±2.07 (-2.80%)	20.26±2.55 (-3.84%)
	Utilization	0.99±0.00 (+2.06%)	0.99±0.00 (+1.02%)	0.99±0.00 (+1.02%)
	WTIT50OT75	1356.02±84.81 (+111.43%)	2559.54±167.59 (+110.91%)	2816.57±208.17 (+89.75%)

For mean duration = 75 minutes (NORA Model Option 3 Mean3), when c_{it} = 1, c_{ot}= 1.5, mean total waiting times, total idle time and overtime are 243.02±15.11, 74.15±3.32 and 42.15±2.98 minutes when expected total costs are lowest. Average waiting time for each patient is 22.09 minutes. Under the condition of c_{it} = 15, c_{ot}= 22.5, mean total waiting times, total idle time and overtime are 792.64±25.60, 14.50±1.57 and 21.07±2.58 minutes when expected total costs are lowest. Average waiting time for each patient will be 72.06 minutes. Patient waiting time for patients increases 226.16% while OR idle time and overtime decrease 80.45% and 50.01%. When c_{it} = 50, c_{ot}= 75, mean total waiting times, total idle time and overtime are 1098.18±29.24, 3.98±0.80 and 20.26±2.55 minutes when expected total costs are lowest. Average waiting time for each patient increases to 99.83 minutes. Patient waiting time increases 38.55% while OR idle time and overtime decrease 72.55% and 3.84%. The results outperform Basic Model Mean3 for expected total costs, which means OR using a NORA policy can perform better when mean durations are higher.

Figure 25 shows the OR schedule for NORA Model Option 3 Mean1. For c_{it} = 1, c_{ot}= 1.5 and c_{it} = 15, c_{ot}= 22.5, patients are scheduled to arrive separately with an interval close to their mean surgery duration. For c_{it} = 50, c_{ot}= 75, patients are scheduled to arrive in a group of two or arrive in a shorter interval. The schedule differs from the Basic Model Mean1 with fewer surgeries to be scheduled close together when c_{it} and c_{ot} are high.

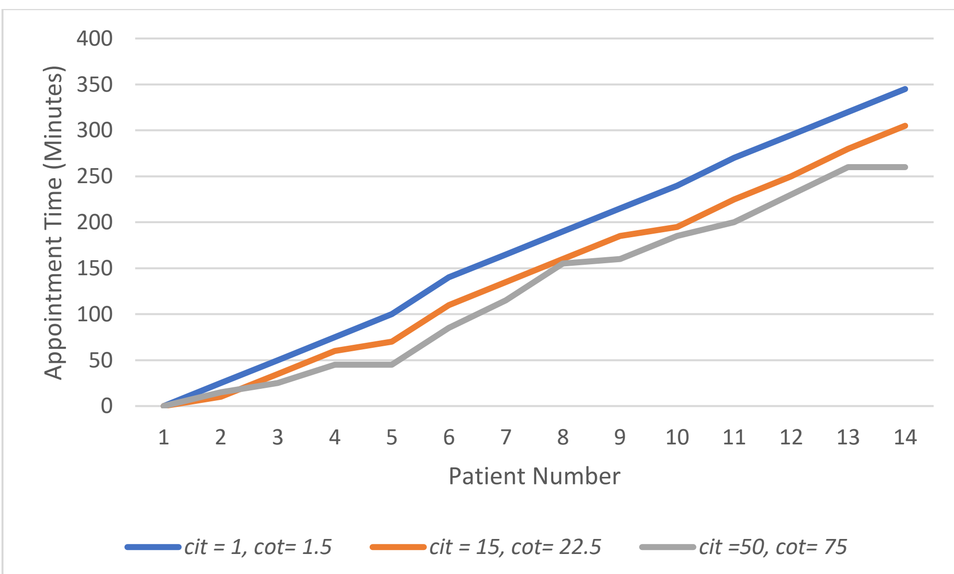

Figure 25. OR Schedule for NORA Model Option 3 Mean1

Figure 26 shows the best OR schedule for NORA Model Option 3 Mean2. For c_{it} = 1, c_{ot}= 1.5, patients are scheduled to arrive separately with an interval close to their mean surgery duration.

For c_{it} = 15, c_{ot}= 22.5 and c_{it} = 50, c_{ot}= 75, patients are scheduled to arrive in a small group of two or three. The main difference of this schedule from the Basic Model Mean2 is that there are more surgeries to be scheduled close together when c_{it} and c_{ot} are lower.

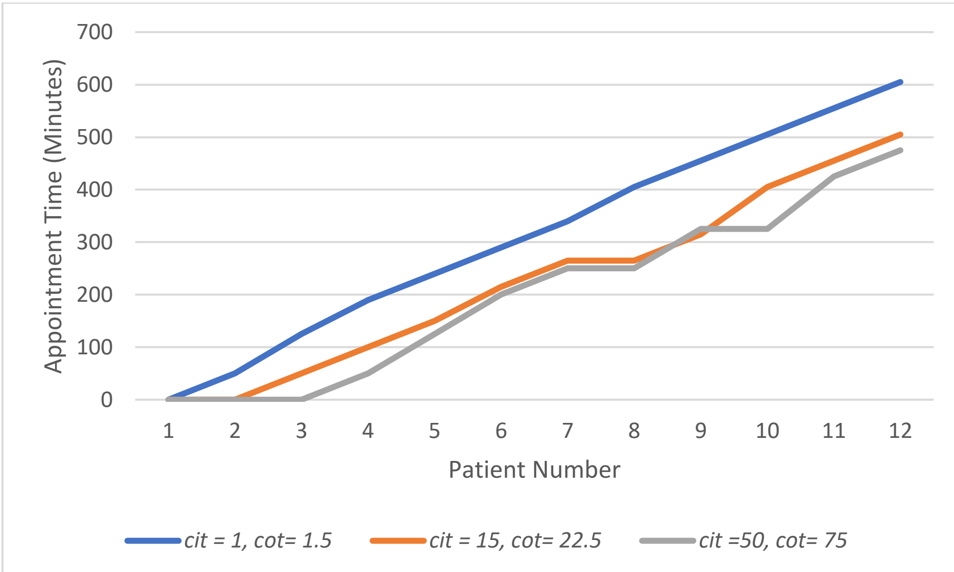

Figure 26. OR Schedule for NORA Model Option 3 Mean2

Figure 27 shows the best OR schedule for NORA Model Option 3 Mean3. For c_{it} = 1, c_{ot}= 1.5, patients are scheduled to arrive separately with an interval close to their mean surgery duration. For c_{it} = 15, c_{ot}= 22.5 and c_{it} = 50, c_{ot}= 75, patients are almost all scheduled to arrive in a small group of two or three. This schedule has much more surgeries scheduled together in groups, which is different from schedules of the Basic Model Mean3.

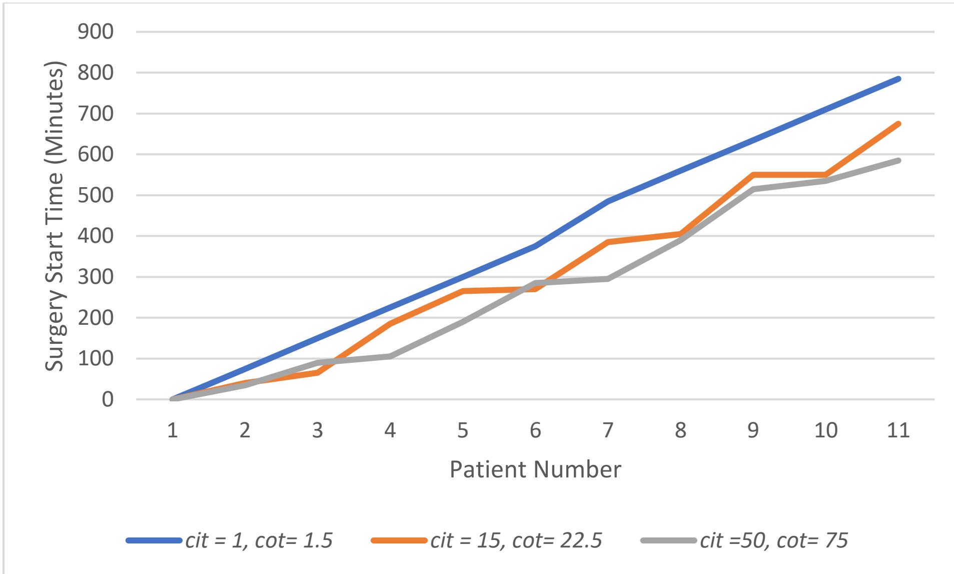

Figure 27. OR Schedule for NORA Model Option 3 Mean3

4.4.4 Comparison of Basic Model and NORA Model for Different Mean Durations

Table 16 shows the key results for the Basic Model and the NORA Models with mean duration = 25 minutes. Comparing the Basic Model Mean1 and the NORA Model Option 2 Mean1, for the settings of c_{it}=1, c_{ot}=1.5, patient waiting time is higher while OR idle time and overtime are lower for NORA Model Option 3 Mean1. ANOVA results (see Appendix Table A14) show that there are significant decreases for performance measure of expected total costs, which means NORA policy can significantly improve OR efficiency. For the settings of c_{it}=15, c_{ot}=22.5 and c_{it}=50, c_{ot}=75, patient waiting time, OR idle time and overtime are all lower for NORA Model Option 3 Mean1. ANOVA results (see Appendix Table A15 and A16) show that there are significant decreases for performance measure of expected total costs, which means a NORA policy can significantly improve OR efficiency.

Comparing the Basic Model Mean1 and the NORA Model Option 3 Mean1, for the settings of c_{it}=1, c_{ot}=1.5, patient waiting time is longer than while OR idle time and overtime are shorter for the NORA Model Option 3 Mean1. ANOVA results (see Appendix Table A14) show that there is a significant increase for performance measure of expected total costs. For the setting of c_{it}=15, c_{ot}=22.5 and c_{it}=50, c_{ot}=75, patient waiting time and OR idle time are longer while OR overtime is shorter for NORA model. According to ANOVA results (see Appendix Table A15 and A16), there are no significant differences for performance measure of expected total costs, which means NORA policy can perform more surgeries within same session length without significantly increase expected total costs. Therefore, NORA models generally perform better in terms of expected total costs when mean durations are shorter.

Table 16. Comparison of Results for Basic Model and NORA Models with Mean Duration =25 minutes

Performance Measures		Basic Model Mean1	NORA Model Option 2 Mean1	NORA Model Option 3 Mean1
c_{it}=1, c_{ot}=1.5	Total Waiting Time	49.70±3.37	54.06±3.80	107.67±6.28
	Total Idle Time	44.36±1.32	29.25±1.17	33.92±1.32
	Overtime	44.01±0.91	28.69±0.89	28.38±1.07
	Utilization	0.89±0.00	0.89±0.00	0.91±0.00
	WTITOT1.5	160.08±3.70	126.35±4.03	184.15±6.73
c_{it}=15, c_{ot}=22.5	Total Waiting Time	249.72±9.13	224.39±7.43	296.27±11.62
	Total Idle Time	6.22±0.50	3.92±0.44	7.46±0.72
	Overtime	12.78±1.12	10.81±0.99	10.37±1.05
	Utilization	0.98±0.00	0.98±0.00	0.97±0.00
	WTIT15OT22.5	630.72±31.09	526.34±26.81	641.36±30.20
c_{it}=50, c_{ot}=75	Total Waiting Time	486.80±9.84	324.38±8.38	505.02±13.45
	Total Idle Time	2.12±0.34	0.86±0.19	2.49±0.37
	Overtime	11.18±1.07	10.18±0.99	9.69±1.03
	Utilization	0.99±0.00	0.99±0.00	0.99±0.00
	WTIT50OT75	1430.99±85.06	1130.57±79.35	1356.02±84.81

Table 17 shows the key results for the Basic Model and the NORA Models with mean duration = 50 minutes. Comparing the Basic Model Mean2 and the NORA Model Option 2 Mean2, for the settings of c_{it}=1, c_{ot}=1.5, patient waiting time is lower while OR idle time and overtime are higher for the NORA Model Option 2 Mean2. ANOVA results (see Appendix Table A18) show that there is no significant difference for performance measure of expected total costs, which means NORA policy can improve OR efficiency without significantly increase expected total costs. For the settings of c_{it}=15, c_{ot}=22.5, patient waiting time is higher while OR idle time and overtime are lower for the NORA Model Option 2 Mean2. ANOVA results (see Appendix Table A19) show that there is no significant difference for performance measure of expected total costs. For the settings of c_{it}=50, c_{ot}=75, patient waiting time and OR overtime are lower while OR idle time is higher for the NORA Model Option 2 Mean2. ANOVA results (see Appendix Table A20) show that there is a significant decrease for performance measure of expected total costs, which means NORA policy can significantly improve OR efficiency.

Comparing the Basic Model Mean2 and the NORA Model Option 3 Mean2, for the settings of c_{it}=1, c_{ot}=1.5, patient waiting time is lower than while OR idle time and overtime are longer for the NORA Model Option 3 Mean2. ANOVA results (see Appendix Table A18) show that there is a significant increase for performance measure of expected total costs, which means NORA policy can improve OR efficiency without significantly increasing expected total costs. For the setting of c_{it}=15, c_{ot}=22.5, patient waiting time are longer while OR idle time and overtime is shorter for NORA model. According to ANOVA results (see Appendix Table A19), there is no significant difference for performance measure of expected total costs, which means NORA policy can perform more surgeries within same session length without significantly increase expected total costs. For the setting of c_{it}=50, c_{ot}=75, patient waiting time and OR overtime is shorter while OR idle time is longer for NORA model. According to ANOVA results (see Appendix Table A20), there is no significant difference for performance measure of expected total costs. The values of expected total costs are not significantly different when scheduling more surgeries in the same session length when c_{it} and c_{ot} are higher. Thus, NORA is still better overall in terms of expected total costs than the Basic Model when mean duration is longer.

Table 17. Comparison of Results for Basic Model and NORA Models with Mean Duration =50 minutes

Performance Measures		Basic Model Mean2	NORA Model Option 2 Mean2	NORA Model Option 3 Mean2
c_{it}=1, c_{ot}=1.5	Total Waiting Time	162.11±10.27	140.86±9.11	140.74±8.59
	Total Idle Time	39.30±1.97	44.06±2.07	80.69±2.48
	Overtime	39.13±2.11	43.06±2.00	74.73±2.06
	Utilization	0.94±0.00	0.92±0.00	0.88±0.00
	WTITOT1.5	260.11±11.56	249.51±10.10	333.52±9.84
c_{it}=15, c_{ot}=22.5	Total Waiting Time	494.61±15.92	606.28±16.19	606.50±20.00
	Total Idle Time	10.94±1.18	5.64±0.82	9.36±1.11
	Overtime	21.92±2.02	20.52±1.98	20.74±2.08
	Utilization	0.98±0.00	0.99±0.00	0.98±0.00
	WTIT15OT22.5	1151.77±53.63	1152.56±54.54	1213.57±58.72
c_{it}=50, c_{ot}=75	Total Waiting Time	911.81±18.35	597.22±16.46	879.01±21.83
	Total Idle Time	1.46±0.33	3.34±0.59	3.37±0.63
	Overtime	20.89±2.02	20.39±1.98	20.16±2.07
	Utilization	0.99±0.00	0.99±0.00	0.99±0.00
	WTIT50OT75	2551.33±163.25	2293.15±156.52	2559.54±167.59

Table 18 shows the key results for the Basic Model and the NORA Models with mean duration = 75 minutes. Comparing the Basic Model Mean3 and the NORA Model Option 2 Mean3, for the settings of c_{it}=1, c_{ot}=1.5, patient waiting time is longer while OR idle time and overtime are shorter for the NORA Model Option 2 Mean3. ANOVA results (see Appendix Table A22) show that there is no significant difference for performance measure of expected total costs. For the settings of c_{it}=15, c_{ot}=22.5 and c_{it}=50, c_{ot}=75, patient waiting time and OR idle time is higher while OR overtime is lower for the NORA Model Option 2 Mean3. ANOVA results (see Appendix Table A23 and A24) show that there are no significant differences for performance measure of expected total costs which means NORA policy can improve OR efficiency without significantly increasing expected total costs.

Comparing the Basic Model Mean3 and the NORA Model Option 3 Mean3, for the settings of c_{it}=1, c_{ot}=1.5, patient waiting time is higher while OR idle time and overtime is lower for the NORA Model Option 3 Mean3. ANOVA results (see Appendix Table A22) show that there is no significant difference for performance measure of expected total costs. For the setting of c_{it}=15, c_{ot}=22.5 and c_{it}=50, c_{ot}=75, patient waiting time are longer while OR idle time and overtime is shorter for NORA model. According to ANOVA results (see Appendix Table A23 and A24), there are no significant differences for performance measure of expected total costs, which means NORA policy can perform more surgeries within same session length with similar costs. Therefore, NORA is better than the Basic Model Mean3 when mean duration is much longer than Basic Model for the reason that it accommodates same number of surgeries within shorter session length or schedules more surgeries within same session length without significantly increase expected total costs.

Table 18. Comparison of Results for Basic Model and NORA Models with Mean Duration =75 minutes

Performance Measures		Basic Model Mean3	NORA Model Option 2 Mean3	NORA Model Option 3 Mean3
c_{it}=1, c_{ot}=1.5	Total Waiting Time	175.37±12.04	199.03±12.70	243.02±15.11
	Total Idle Time	82.78±3.32	71.96±3.18	74.15±3.32
	Overtime	81.31±2.90	70.35±3.01	42.15±2.98
	Utilization	0.91±0.00	0.91±0.00	0.92±0.00
	WTITOT1.5	380.12±13.46	376.51±14.25	384.90±16.49
c_{it}=15, c_{ot}=22.5	Total Waiting Time	600.66±24.03	660.38±21.83	792.64±25.60
	Total Idle Time	11.08±1.12	14.65±141	14.50±1.57
	Overtime	33.44±3.06	33.28±3.03	21.07±2.58
	Utilization	0.99±0.00	0.98±0.00	0.98±0.00
	WTIT15OT22.5	1519.09±84.64	1628.98±80.33	1484.34±72.90
c_{it}=50, c_{ot}=75	Total Waiting Time	807.28±26.83	901.54±25.33	1098.18±29.24
	Total Idle Time	2.82±0.59	2.99±0.65	3.98±0.80
	Overtime	31.08±3.01	30.59±2.99	20.26±2.55
	Utilization	0.99±0.00	0.99±0.00	0.99±0.00
	WTIT50OT75	3278.81±241.81	3344.87±238.49	2816.57±208.17

Overall, the NORA Model Option 2 performs better than the Basic Model in terms of OR performance. NORA Option 3 results in a higher expected total cost when coefficients of OR idle time and overtime have lower weights. However, more surgeries are performed in the same session length compared to the Basic Model. Therefore, NORA model is still better overall in terms of expected total costs especially when OR idle time and overtime have higher weights of coefficients.

5 Conclusion

In this thesis, non-operating room anesthesia (NORA) is considered as a strategy for improving OR performance in terms of patient waiting time, OR idle time and OR overtime. A NORA policy allows the anesthesia stage to be performed outside OR, which gives potential of improving OR efficiency without significantly increasing expected total costs. NORA policies allow ORs to save time and schedule more surgeries when compared with traditional OR scheduling. This thesis explores how a NORA policy can improve OR performance in a general single-OR setting with different cost coefficients for OR idle time and overtime. Using the data from CIHI to validate the inputs of this study, various scenarios considering different standard deviation values and mean durations are simulated.

Table 19. Comparison of Expected Total Costs for Basic Model and NORA Model

Performance Measures	Basic Model	NORA Model Option2	NORA Model Option 3
c_{it}=1, c_{ot}=1.5	175.58±5.44	160.61±4.76	223.05±6.18
c_{it}=15, c_{ot}=22.5 (Percentage compared to c_{it} = 1, c_{ot}= 1.5)	804.76±38.26 (+358.34%)	800.13±42.79 (+398.18%)	1268.86±45.07 (+468.87%)
c_{it}=50, c_{ot}=75 (Percentage compared to c_{it} = 1, c_{ot}= 1.5)	1742.45±106.86 (+116.52%)	1703.87±98.62 (+112.95%)	1629.69±98.73 (+28.44%)

Table 14 shows a summary for expected total costs of the Basic Model and NORA Models. The results show that a NORA policy can significantly reduce total costs when number of surgery appointments and session length stay the same mostly because overtime and waiting time decrease due to shorter surgery duration in OR. NORA policy is beneficial when same number of surgery appointments are performed in shorter session length. Total costs are not significantly different while OR times are saved. This result is also true when the condition of same session length is kept and more surgeries are performed. Expected OR costs for performing more surgeries are not far from costs of original number of surgery appointments. In particular, as the cost of OR resources goes up, NORA produces better results for OR idle time and overtime, which is beneficial for hospitals to improve OR efficiency.

One of the most notable variations in OR scheduling is surgery duration due to different conditions of hospital resources. Different standard deviations for the distributions for surgery duration generated can be a major factor in OR performance. A NORA policy shows a significant improvement when standard deviation of surgery durations increases. The results showed that for larger standard deviation values, OR performance were close to basic situation when the session length was reduced for the same number of surgery appointments and when a larger number of surgeries were scheduled for the same session length. Therefore, when there is more variability in surgery duration, NORA can improve performance because it offers room for changing either number of surgeries or session length. It is reasonable to believe that NORA policy is a more flexible policy for scheduling surgeries.

Mean duration of surgery procedures is another important factor that can impact OR performance. Data generated from this thesis produced a mean duration of 42 minutes. However, other types of surgeries can be different. Lower and higher mean durations were tested to determine the impact of this factor on performance of the OR. The results showed that a NORA policy provides a good fit with a wide range of mean surgery durations. Expected total costs are lower in many scenarios. Longer mean durations tend to perform worse in OR efficiency, while NORA policy can reduce the effect of longer durations. Overall, NORA policy is suitable for improving OR efficiency under numerous conditions. It is a flexible policy and it is beneficial in terms of OR efficiency and total costs.

There are several limitations for this thesis. The first is that this thesis only considers the difference of expected total costs in OR. Performing anesthesia stage outside OR certainly requires some resources and creates costs. These types of costs are ignored in this thesis. The second is that the result produced by this paper come from one types of surgery. Though we use experiments on standard deviation and means, the combination of these stats is still based on this type of surgery. It is not guaranteed that NORA policy can also have great performance when combination changes.

References

Adan, I., & Vissers, J. (2002). Patient mix optimization in hospital admission planning: a case study. International Journal of Operations & Production Management, 22(4), 445–461. https://doi.org/10.1108/01443570210420430

Adan, I., Bekkers, J., Dellaert, N., Vissers, J., & Yu, X. (2008). Patient mix optimization and stochastic resource requirements: A case study in cardiothoracic surgery planning. Health Care Management Science, 12(2), 129. https://doi.org/10.1007/s10729-008-9080-9

Batun, S., Denton, B. T., Huschka, T. R., & Schaefer, A. J. (2011). Operating Room Pooling and Parallel Surgery Processing Under Uncertainty. INFORMS Journal on Computing, 23(2), 220–237. https://doi.org/10.1287/ijoc.1100.0396

Bekker, R., & Koeleman, P. (2011). Scheduling admissions and reducing variability in bed demand. Health Care Management Science, 14(3), 237–249. https://doi.org/10.1007/s10729-011-9163-x

Beliën, J., & Demeulemeester, E. (2008). A branch-and-price approach for integrating nurse and surgery scheduling. European Journal of Operational Research, 189(3), 652–668. https://doi.org/10.1016/j.ejor.2006.10.060

Beliën, J., Demeulemeester, E., & Cardoen, B. (2008). A decision support system for cyclic master surgery scheduling with multiple objectives. Journal of Scheduling, 12(2), 147. https://doi.org/10.1007/s10951-008-0086-4

Blake, J. T., & Carter, M. W. (2002). A goal programming approach to strategic resource allocation in acute care hospitals. European Journal of Operational Research, 140(3), 541–561. https://doi.org/10.1016/S0377-2217(01)00219-3

Blake, J. T., Dexter, F., & Donald, J. (2002). Operating Room Managers' Use of Integer Programming for Assigning Block Time to Surgical Groups: A Case Study. Anesthesia & Analgesia, 94(1), 143. https://doi.org/10.1213/00000539-200201000-00027

Buchanan, D., & Wilson, B. (1996). Re-engineering operating theatres: The perspective assessed. Journal of Management in Medicine, 10(4), 57-74. Retrieved from http://proxy.library.brocku.ca/login?url=https://search.proquest.com/docview/197375582?accountid=9744

Burgette, L., Mulcahy, A., Mehrotra, A., Ruder, T., & Wynn, B. (2017). Estimating Surgical Procedure Times Using Anesthesia Billing Data and Operating Room Records. Health Services Research, 52(1), 74–92. https://doi.org/10.1111/1475-6773.12474

Canadian Institute for Health Information (2018). National Health Expenditure Trends, 1975 to 2018. Ottawa, ON: CIHI. Retrieved from https://www.cihi.ca/sites/default/files/document/nhex-trends-narrative-report-2018-en-web.pdf

Cardoen, B., & Demeulemeester, E. (2008). Capacity of Clinical Pathways—A Strategic Multi-level Evaluation Tool. Journal of Medical Systems, 32(6), 443–452. https://doi.org/10.1007/s10916-008-9150-z

Cardoen, B., Demeulemeester, E., & Beliën, J. (2009). Optimizing a multiple objective surgical case sequencing problem. International Journal of Production Economics, 119(2), 354–366. https://doi.org/10.1016/j.ijpe.2009.03.009

Cardoen, B., Demeulemeester, E., & Beliën, J. (2010). Operating room planning and scheduling: A literature review. European Journal of Operational Research, 201(3), 921–932. https://doi.org/10.1016/j.ejor.2009.04.011

Cayirli, T., & Veral, E. (2003). Outpatient Scheduling in Health Care: A Review of Literature. Production & Operations Management, 12(4), 519–549.

Cayirli, T., & Gunes, E. D. (2014). Outpatient appointment scheduling in presence of seasonal walk-ins. The Journal of the Operational Research Society, 65(4), 512-531. http://dx.doi.org/10.1057/jors.2013.56

Chang, B., Kaye, A. D., Diaz, J. H., Westlake, B., Dutton, R. P., & Urman, R. D. (2018). Interventional Procedures Outside of the Operating Room: Results From the National Anesthesia Clinical Outcomes Registry. Journal of Patient Safety, (1), 9. https://doi.org/10.1097/PTS.0000000000000156

Chen, T.-L., Chen, J. C., Huang, C.-F., & Chang, P.-C. (2021). Solving the layout design problem by simulation-optimization approach–A case study on a sortation conveyor system. Simulation Modelling Practice and Theory, 106, 102192–. https://doi.org/10.1016/j.simpat.2020.102192

Costa, J. (2017). Assessment of operative times of multiple surgical specialties in a public university hospital. Einstein (São Paulo, Brazil), 15(2), 200–205. https://doi.org/10.1590/s1679-45082017gs3902

Denton, B., & Gupta, D. (2003). A Sequential Bounding Approach for Optimal Appointment Scheduling. IIE Transactions, 35(11), 1003–1016. https://doi.org/10.1080/07408170304395

Denton, B. T., Rahman, A. S., Nelson, H., & Bailey, A. C. (2006). Simulation of a Multiple Operating Room Surgical Suite. Proceedings of the 2006 Winter Simulation Conference, 414–424. https://doi.org/10.1109/WSC.2006.323110

Denton, B., Viapiano, J., & Vogl, A. (2007). Optimization of surgery sequencing and scheduling decisions under uncertainty. Health Care Management Science, 10(1), 13–24. https://doi.org/10.1007/s10729-006-9005-4

Dexter, F., Macario, A., Traub, R., Hopwood, M., & Lubarsky, D. (1999) An Operating Room Scheduling Strategy to Maximize the Use of Operating Room Block Time. Anesthesia & Analgesia, 89(1) ,7-20. https://doi.org/10.1213/00000539-199907000-00003

Dexter, F. (2000). A strategy to decide whether to move the last case of the day in an operating room to another empty operating room to decrease overtime labor costs. Anesthesia and Analgesia, 91(4), 925–928. https://doi.org/10.1097/00000539-200010000-00029

Dexter, F., Lubarsky, D. A., & Blake, J. T. (2002). Sampling Error Can Significantly Affect Measured Hospital Financial Performance of Surgeons and Resulting Operating Room Time Allocations. Anesthesia & Analgesia, 95(1), 184. https://doi.org/10.1097/00000539-200207000-00032

Dexter, F., & Macario, A. (2004). When to Release Allocated Operating Room Time to Increase Operating Room Efficiency. Anesthesia & Analgesia, 98(3), 758. https://doi.org/10.1213/01.ANE.0000100739.03919.26

Dexter, F., & Traub, R. (2002). How to Schedule Elective Surgical Cases into Specific Operating Rooms to Maximize the Efficiency of Use of Operating Room Time. Anesthesia & Analgesia, 94(4), 933–942. https://doi.org/10.1097/00000539-200204000-00030

Erdogan, S. A., & Denton, B. T. (2011). Surgery planning and scheduling. Wiley Encyclopedia of Operations Research and Management Science.

Etzioni, David A. (2003). The Aging Population and Its Impact on the Surgery Workforce. Annals of Surgery, 238(2), 170. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=edo&AN=12077515&site=eds-live&scope=site

Everett, J. E. (2002). A Decision Support Simulation Model for the Management of an Elective Surgery Waiting System. Health Care Management Science, 5(2), 89–95. https://doi.org/10.1023/A:1014468613635

Fei, H., Chu, C., Meskens, N., & Artiba, A. (2008). Solving surgical cases assignment problem by a branch-and-price approach. International Journal of Production Economics, 112(1), 96–108. https://doi.org/10.1016/j.ijpe.2006.08.030

Fei, H., Chu, C., & Meskens, N. (2009). Solving a tactical operating room planning problem by a column-generation-based heuristic procedure with four criteria. Annals of Operations Research; New York, 166(1), 91–108. http://dx.doi.org/10.1007/s10479-008-0413-3

Fei, H., Meskens, N., & Chu, C. (2010). A planning and scheduling problem for an operating theatre using an open scheduling strategy. Computers & Industrial Engineering, 58(2), 221. Retrieved from http://proxy.library.brocku.ca/login?url=https://search-proquest-com.proxy.library.brocku.ca/docview/213750599?accountid=9744

Guerriero, F., & Guido, R. (2011). Operational research in the management of the operating theatre: A survey. Health Care Management Science; New York, 14(1), 89–114. http://dx.doi.org/10.1007/s10729-010-9143-6

Guinet, A., & Chaabane, S. (2003). Operating theatre planning. International Journal of Production Economics, 85(1), 69–81. https://doi.org/10.1016/S0925-5273(03)00087-2

Gupta, D., & Denton, B. (2008). Appointment scheduling in health care: Challenges and opportunities. IIE Transactions, 40(9), 800–819. https://doi.org/10.1080/07408170802165880

Haeussler, S., & Netzer, P. (2020). Comparison between rule- and optimization-based workload control concepts: a simulation optimization approach. International Journal of Production Research, 58(12), 3724–3743. https://doi.org/10.1080/00207543.2019.1634297

Isgett-Lynn, B. (2011). Improving patient prep. Health Management Technology, 32(3), 24–26.

Jebali, A., Hadj Alouane, A. B., & Ladet, P. (2006). Operating rooms scheduling. International Journal of Production Economics, 99(1), 52–62. https://doi.org/10.1016/j.ijpe.2004.12.006

Jebali, A., & Diabat, A. (2017). A Chance-constrained operating room planning with elective and emergency cases under downstream capacity constraints. Computers & Industrial Engineering, 114, 329–344. https://doi.org/10.1016/j.cie.2017.07.015

Kayis, E., Wang, H., Patel, M., Gonzalez, T., Jain, S., Ramamurthi, R. J., Sylvester, K. (2012). Improving prediction of surgery duration using operational and temporal factors. AMIA Annual Symposium proceedings. AMIA Symposium, 2012, 456–462.

Khlif Hachicha, H., Khlif Hachicha, H., Zeghal Mansour, F., & Zeghal Mansour, F. (2018). Two-MILP models for scheduling elective surgeries within a private healthcare facility. Health Care Management Science, 21(3), 376–392. https://doi.org/10.1007/s10729-016-9390-2

Klassen, K. J., & Yoogalingam, R. (2009). Improving performance in outpatient appointment services with a simulation optimization approach. Production and Operations Management, 18(4), 447-458. Retrieved from http://proxy.library.brocku.ca/login?url=https://search.proquest.com/docview/853335149?accountid=9744

Lamiri, M., Dreo, J., & Xie, X. (2007). Operating Room Planning with Random Surgery Times. 2007 IEEE International Conference on Automation Science and Engineering, 521–526. https://doi.org/10.1109/COASE.2007.4341749

Lamiri, M., Grimaud, F., & Xie, X. (2009). Optimization methods for a stochastic surgery planning problem. International Journal of Production Economics, 120(2), 400–410. https://doi.org/10.1016/j.ijpe.2008.11.021

Lamiri, M., Xie, X., Dolgui, A., & Grimaud, F. (2008). A stochastic model for operating room planning with elective and emergency demand for surgery. European Journal of Operational Research, 185(3), 1026–1037. https://doi.org/10.1016/j.ejor.2006.02.057

Laguna, M. (1997a). Metaheuristic optimization with evolver, genocop and optquest. In EURO/INFORMS Joint International Meeting, Plenaries and Tutorials (pp. 141–150).

Laguna, M. (1997b). Optimization of complex systems with OptQuest. A White Paper from OptTek Systems, Inc.

Liang, F., Guo, Y., & Fung, R. Y. K. (2015). Simulation-Based Optimization for Surgery Scheduling in Operation Theatre Management Using Response Surface Method. Journal of Medical Systems, 39(11), 1–11. https://doi.org/10.1007/s10916-015-0349-5

Liu, H., Zhang, T., Luo, S., & Xu, D. (2018). Operating room scheduling and surgeon assignment problem under surgery durations uncertainty. Technology & Health Care, 26(2), 297–304. https://doi.org/10.3233/THC-170825

Lovejoy, W. S., & Li, Y. (2002). Hospital Operating Room Capacity Expansion. Management Science, 48(11), 1369–1387. https://doi.org/10.1287/mnsc.48.11.1369.266

Ma, G., Belien, J., Demeulemeester, E., & Wang, L. (2009). Solving the strategic case mix problem optimally by using branch-and-price algorithms.

Marcela Diaz-Lopez, D., Andres Lopez-Valencia, N., Maria Gonzalez-Neira, E., Barrera, D., Suarez, D. R., Patricia Caro-Gutierrez, M., & Sefair, C. (2018). A simulation-optimization approach for the surgery scheduling problem: a case study considering stochastic surgical times. International Journal of Industrial Engineering Computations, 9(4), 409–422. https://doi.org/10.5267/j.ijiec.2018.1.002

Marques, I., Captivo, M. E., & Vaz Pato, M. (2012). An integer programming approach to elective surgery scheduling. OR Spectrum, 34(2), 407–427. https://doi.org/10.1007/s00291-011-0279-7

May, J. H., Spangler, W. E., Strum, D. P., & Vargas, L. G. (2011). The Surgical Scheduling Problem: Current Research and Future Opportunities. Production & Operations Management, 20(3), 392–405. https://doi.org/10.1111/j.1937-5956.2011.01221.x

Nagrebetsky, A., Gabriel, R. A., Dutton, R. P., & Urman, R. D. (2017). Growth of Nonoperating Room Anesthesia Care in the United States: A Contemporary Trends Analysis. Anesthesia & Analgesia, 124(4), 1261. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=edb&AN=121966761&site=eds-live&scope=site

Ogulata, S. N., & Erol, R. (2003). A Hierarchical Multiple Criteria Mathematical Programming Approach for Scheduling General Surgery Operations in Large Hospitals. Journal of Medical Systems, 27(3), 259–270. https://doi.org/10.1023/A:1022575412017

OptQuest (Version 5.1.1.2) Computer software . OptTek Systems, Inc.

OptQuest Guide (2017). Oracle Crystal Ball Decision Optimizer OptQuest User's Guide. https://docs.oracle.com/cd/E57185_01/CBOUG/index.html

Ozkarahan, I. (2000). Allocation of Surgeries to Operating Rooms by Goal Programing. Journal of Medical Systems, 24(6), 339–378. https://doi.org/10.1023/A:1005548727003

Paoletti, X., & Marty, J. (2007). Consequences of running more operating theatres than anaesthetists to staff them: A stochastic simulation study. British Journal of Anaesthesia, 98(4), 462–469. https://doi.org/10.1093/bja/aem003

Patterson P. (1996). OR scheduling. What makes a well-oiled scheduling system? OR Manager, 12(9), 19–23. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=cin20&AN=107350411&site=eds-live&scope=site

Persson, M., & Persson, J. A. (2009). Health economic modeling to support surgery management at a Swedish hospital. Omega, 37(4), 853–863. https://doi.org/10.1016/j.omega.2008.05.007

Phan, P., Lee, S.-H., Dai, T., Moran, N., Mathuranayagam, V. J., & Stonemetz, J. (2018). Exploratory Study of Factors Influencing Surgery Scheduled Length, Deviation from Scheduled Length, and Impact on Length of Stay. Journal of the American College of Surgeons, 227(4), e160. https://doi.org/10.1016/j.jamcollsurg.2018.08.436

Puffer, R. C., Mallory, G. W., Burrows, A. M., Curry, T. B., & Clarke, M. J. (2016). Patient and Procedural Factors That Influence Anesthetized, Nonoperative Time in Spine Surgery. Global Spine Journal, 6(5), 447–451. https://doi.org/10.1055/s-0035-1564808

Pulido, R., Aguirre, A., Ortega-Mier, M., García-Sánchez, Á., & Méndez, C. (2014). Managing daily surgery schedules in a teaching hospital: a mixed-integer optimization approach. BMC Health Services Research, 14(1), 464–464. https://doi.org/10.1186/1472-6963-14-464

Rockwell Automation. (2005). OptQuest for Arena User’s Guide

Saremi, A., Jula, P., ElMekkawy, T., & Wang, G. G. (2013). Appointment scheduling of outpatient surgical services in a multistage operating room department. International Journal of Production Economics, 141(2), 646–658. https://doi.org/10.1016/j.ijpe.2012.10.004

Santibanez, P., Begen, M., & Atkins, D. (2007). Surgical Block Scheduling in a System of Hospitals: An Application to Resource and Wait List Management in a British Columbia Health Authority. Health Care Management Science, 10(3), 269–282.

Singh, A. (2014). Simulation–optimization modeling for conjunctive water use management. Agricultural Water Management, 141, 23–29. https://doi.org/10.1016/j.agwat.2014.04.003

Testi, A., Tanfani, E., & Torre, G. (2007). A three-phase approach for operating theatre schedules. Health Care Management Science, 10(2), 163–172.

Van Berkel, P. T., & Blake, J. T. (2007). A comprehensive simulation for wait time reduction and capacity planning applied in general surgery. Health Care Management Science, 10(4), 373–385. https://doi.org/10.1007/s10729-007-9035-6

Van Essen, J. T., Hurink, J. L., Hartholt, W., & van den Akker, B. J. (2012). Decision support system for the operating room rescheduling problem. Health Care Management Science; New York, 15(4), 355–372. http://dx.doi.org/10.1007/s10729-012-9202-2

Vissers, J., Adan, I., & Bekkers, J. (2005). Patient mix optimization in tactical cardiothoracic surgery planning: A case study. Ima Journal of Management Mathematics - IMA J MANAG MATH. 16. 281-304. 10.1093/imaman/dpi023.

Wang, D., Liu, F., Yin, Y., Wang, J., & Wang, Y. (2015). Prioritized surgery scheduling in face of surgeon tiredness and fixed off-duty period. Journal of Combinatorial Optimization, 30(4), 967–981. https://doi.org/10.1007/s10878-015-9846-1

Weinbroum, A. A., Ekstein, P., & Ezri, T. (2003). Efficiency of the operating room suite. The American Journal of Surgery, 185(3), 244–250. https://doi.org/10.1016/S0002-9610(02)01362-4

Wong, T., Georgiadis, P. L., Urman, R. D., & Tsai, M. H. (2020). Non-Operating Room Anesthesia: Patient Selection and Special Considerations. Local and regional anesthesia, 13, 1–9. https://doi.org/10.2147/LRA.S181458

Woodward, Z. G., Urman, R. D., & Domino, K. B. (2017). Safety of Non–Operating Room Anesthesia: A Closed Claims Update. Anesthesiology Clinics, 35(4), 569–581. https://doi.org/10.1016/j.anclin.2017.07.003

Zhang, B., Murali, P., Dessouky, M. M., & Belson, D. (2009). A mixed integer programming approach for allocating operating room capacity. Journal of the Operational Research Society, 60(5), 663–673. https://doi.org/10.1057/palgrave.jors.2602596

Zhang, Z., Xie, X., & Geng, N. (2014). Dynamic Surgery Assignment of Multiple Operating Rooms With Planned Surgeon Arrival Times. IEEE Transactions on Automation Science and Engineering, 11(3), 680–691. https://doi.org/10.1109/TASE.2013.2267273

Appendices

Label	Basic Model	NORA Model Option 1	NORA Model Option 2	NORA Model Option 3
c_{it}=1, c_{ot}=1.5	M11	M12	M13	M14
c_{it}=15, c_{ot}=22.5	M21	M22	M23	M24
c_{it}=50, c_{ot}=75	M31	M32	M33	M34

Table A1. Model labels for Tests from Table A2-A4

Dependent Variable: M11						
Tukey HSD						
(I) Weights	(J) Weights	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
M11	M12	25.181*	7.217	.003	6.609	43.753
	M13	13.797	7.217	.224	-4.775	32.369
	M14	-45.164*	7.217	.000	-63.736	-26.592
M12	M11	-25.181*	7.217	.003	-43.753	-6.609
	M13	-11.384	7.217	.392	-29.956	7.188
	M14	-70.345*	7.217	.000	-88.917	-51.773
M13	M11	-13.797	7.217	.224	-32.369	4.775
	M12	11.384	7.217	.392	-7.188	29.956
	M14	-58.961*	7.217	.000	-77.533	-40.389
M14	M11	45.164*	7.217	.000	26.592	63.736
	M12	70.345*	7.217	.000	51.773	88.917
	M13	58.961*	7.217	.000	40.389	77.533
*. The mean difference is significant at the 0.05 level.						

Table A2. ANOVA tests of total costs for c_{it}=1, c_{ot}=1.5 from 4.2

Dependent Variable: M21						
Tukey HSD						
(I) Weights	(J) Weights	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
M21	M22	514.620*	45.490	.000	397.556	631.683
	M23	144.750*	45.490	.008	27.687	261.813
	M24	-307.173*	45.490	.000	-424.237	-190.110
M22	M21	-514.620*	45.490	.000	-631.683	-397.556
	M23	-369.869*	45.490	.000	-486.933	-252.806
	M24	-821.793*	45.490	.000	-938.856	-704.730
M23	M21	-144.750*	45.490	.008	-261.813	-27.687
	M22	369.869*	45.490	.000	252.806	486.933
	M24	-451.923*	45.490	.000	-568.987	-334.860
M14	M21	307.173*	45.490	.000	190.110	424.237
	M22	821.193*	45.490	.000	704.730	938.856
	M23	451.923*	45.490	.000	334.860	568.987
*. The mean difference is significant at the 0.05 level.						

Table A3. ANOVA tests of total costs for c_{it}=15, c_{ot}=22.5 from 4.2

Dependent Variable: M31						
Tukey HSD						
(I) Weights	(J) Weights	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
M31	M32	1317.340*	126.273	.000	992.391	1642.288
	M33	48.826	126.273	.980	-276.122	373.775
	M34	203.654	126.273	.372	-121.295	528.603
M32	M31	-1317.340*	126.273	.000	-1642.288	-992.391
	M33	-1268.513*	126.273	.000	-1593.462	-943.564
	M34	-1113.686*	126.273	.000	-1438.634	-788.737
M33	M31	-48.826	126.273	.980	-373.775	276.122
	M32	1268.513*	126.273	.000	943.564	1593.462
	M34	154.828	126.273	.610	-170.121	479.776
M34	M31	-203.654	126.273	.372	-528.603	121.295
	M32	1113.686*	126.273	.000	788.737	1438.634
	M33	-154.828	126.273	.610	-479.776	170.121
*. The mean difference is significant at the 0.05 level.						

Table A4. ANOVA tests of total costs for c_{it}=50, c_{ot}=75 from 4.2

Label STD=15minutes	Basic Model STD1	NORA Model Option 2 STD1	NORA Model Option 3 STD1
c_{it}=1, c_{ot}=1.5	B11	B12	B13
c_{it}=15, c_{ot}=22.5	B21	B22	B23
c_{it}=50, c_{ot}=75	B31	B32	B33

Table A5. Model labels for Tests from Table A6-A8

Dependent Variable: B11						
Tukey HSD						
(I) Weights	(J) Weights	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
B11	B12	13.829	14.900	.623	-21.162	48.820
	B13	-49.690*	14.900	.003	-84.681	-14.699
B12	B11	-13.829	14.900	.623	-48.820	21.162
	B13	-63.519*	14.900	.000	-98.510	-28.527
B13	B11	49.690*	14.900	.003	14.699	84.681
	B12	63.519*	14.900	.000	28.527	98.510
*. The mean difference is significant at the 0.05 level.						

Table A6. ANOVA tests of total costs for c_{it}=1, c_{ot}=1.5 and std=15 from 4.3

Dependent Variable: B21						
Tukey HSD						
(I) Weights	(J) Weights	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
B21	B22	82.569	74.225	.507	-91.742	256.879
	B23	-89.648	74.225	.449	-263.959	84.662
B22	B21	-82.569	74.225	.507	-256.879	91.742
	B23	-172.217	74.225	.054	-346.527	2.093
B23	B21	89.648	74.225	.449	-84.662	263.959
	B22	172.217	74.225	.054	-2.093	346.527
*. The mean difference is significant at the 0.05 level.						

Table A7. ANOVA tests of total costs for c_{it}=15, c_{ot}=22.5 and std=15 from 4.3

Dependent Variable: B31						
Tukey HSD						
(I) Weights	(J) Weights	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
B31	B32	54.177	211.788	.965	-443.194	551.539
	B33	20.526	211.788	.995	-476.835	517.888
B32	B31	-54.177	211.788	.965	-551.539	443.184
	B33	-33.651	211.788	.986	-531.013	463.711
B33	B31	-20.526	211.788	.995	-517.888	476.835
	B32	33.651	211.788	.986	-463.711	531.013

Table A8. ANOVA tests of total costs for c_{it}=50, c_{ot}=75 and std=15 from 4.3

Label STD=20minutes	Basic Model STD2	NORA Model Option 2 STD2	NORA Model Option 3 STD2
c_{it}=1, c_{ot}=1.5	BA11	BA12	BA13
c_{it}=15, c_{ot}=22.5	BA21	BA22	BA23
c_{it}=50, c_{ot}=75	BA31	BA32	BA33

Table A9. Model labels for Tests from Table A10-A12

Dependent Variable: BA11						
Tukey HSD						
(I) Weights	(J) Weights	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
BA11	BA12	13.026	22.459	.831	-39.718	65.769
	BA13	-80.977*	22.459	.001	-133.720	-28.234
BA12	BA11	-13.026	22.459	.831	-65.769	39.718
	BA13	-94.003*	22.459	.000	-146.746	-41.259
BA13	BA11	80.977*	22.459	.001	28.234	133.720
	BA12	94.003*	22.459	.000	41.259	146.746
*. The mean difference is significant at the 0.05 level.						

Table A10. ANOVA tests of total costs for c_{it}=1, c_{ot}=1.5 and std=20 from 4.3

Dependent Variable: BA21						
Tukey HSD						
(I) Weights	(J) Weights	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
BA21	BA22	45.797	100.276	.891	-189.690	281.284
	BA23	-290.489	100.276	.011	-525.977	-55.002
BA22	BA21	-45.797	100.276	.891	-281.284	189.690
	BA23	-336.286	100.276	.002	-571.774	-100.799
BA23	BA21	290.489	100.276	.011	55.002	525.977
	BA22	336.286	100.276	.002	100.799	571.774
*. The mean difference is significant at the 0.05 level.						

Table A11. ANOVA tests of total costs for c_{it}=15, c_{ot}=22.5 and std=20 from 4.3

Dependent Variable: BA31						
Tukey HSD						
(I) Weights	(J) Weights	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
BA31	BA32	66.714	292.520	.972	-620.238	753.666
	BA33	-35.404	292.520	.992	-722.356	651.548
BA32	BA31	-66.714	292.520	.972	-753.666	620.238
	BA33	-102.118	292.520	.935	-789.070	584.834
BA33	BA31	35.404	292.520	.992	-651.548	722.356
	BA32	102.118	292.520	.935	-584.834	789.070

Table A12. ANOVA tests of total costs for c_{it}=50, c_{ot}=75 and std=20 from 4.3

Label Mean=25minutes	Basic Model Mean1	NORA Model Option 2 Mean1	NORA Model Option 3 Mean1
c_{it}=1, c_{ot}=1.5	MA11	MA12	MA13
c_{it}=15, c_{ot}=22.5	MA21	MA22	MA23
c_{it}=50, c_{ot}=75	MA31	MA32	MA33

Table A13. Model labels for Table A14-A16

Dependent Variable: MA11						
Tukey HSD						
(I) Weights	(J) Weights	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
MA11	MA12	32.346*	7.334	.000	15.123	49.569
	MA13	-21.430*	7.334	.010	-38.653	-4.206
MA12	MA11	-32.346*	7.334	.000	-49.569	-15.123
	MA13	-53.776*	7.334	.000	-70.999	-36.552
MA13	MA11	21.430*	7.334	.010	4.206	38.653
	MA12	53.776*	7.334	.000	36.552	70.999
*. The mean difference is significant at the 0.05 level.						

Table A14. ANOVA tests of total costs for c_{it}=1, c_{ot}=1.5 and Mean 25 minutes

Dependent Variable: MA21						
Tukey HSD						
(I) Weights	(J) Weights	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
MA21	MA22	134.791*	42.929	.005	33.977	235.605
	MA23	30.545	42.929	.757	-70.269	131.360
MA22	MA21	-134.791*	42.929	.005	-235.605	-33.977
	MA23	-104.246*	42.929	.041	-205.060	-3.432
MA23	MA21	-30.545	42.929	.757	-131.360	70.269
	MA22	104.246*	42.929	.041	3.432	205.060
*. The mean difference is significant at the 0.05 level.						

Table A15. ANOVA tests of total costs for c_{it}=15, c_{ot}=22.5 and Mean 25 minutes

Dependent Variable: MA31						
Tukey HSD						
(I) Weights	(J) Weights	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
MA31	MA32	305.192*	119.750	.030	23.972	586.412
	MA33	109.805	119.750	.630	-171.416	391.025
MA32	MA31	-305.192*	119.750	.030	-586.412	-23.972
	MA33	-195.387	119.750	.233	-476.608	85.833
MA33	MA31	-109.805	119.750	.630	-391.025	171.416
	MA32	195.387	119.750	.233	-85.833	476.608
*. The mean difference is significant at the 0.05 level.						

Table A16. ANOVA tests of total costs for c_{it}=50, c_{ot}=75 and Mean 25 minutes

Label Mean=50minutes	Basic Model Mean2	NORA Model Option 2 Mean2	NORA Model Option 3 Mean2
c_{it}=1, c_{ot}=1.5	MB11	MB12	MB13
c_{it}=15, c_{ot}=22.5	MB21	MB22	MB23
c_{it}=50, c_{ot}=75	MB31	MB32	MB33

Table A17. Model labels for Table A18-A20

Dependent Variable: MB11						
Tukey HSD						
(I) Weights	(J) Weights	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
MB11	MB12	12.855	15.530	.686	-23.615	49.324
	MB13	-60.587*	15.530	.000	-97.057	-24.118
MB12	MB11	-12.855	15.530	.686	-49.324	23.615
	MB13	-73.442*	15.530	.000	-109.911	-36.973
MB13	MB11	60.587*	15.530	.000	24.118	97.057
	MB12	73.442*	15.530	.000	36.973	109.911
*. The mean difference is significant at the 0.05 level.						

Table A18. ANOVA tests of total costs for c_{it}=1, c_{ot}=1.5 and Mean 50 minutes

Dependent Variable: MB21						
Tukey HSD						
(I) Weights	(J) Weights	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
MB21	MB22	-13.325	79.885	.985	-200.926	174.276
	MB23	-41.737	79.885	.860	-229.338	145.864
MB22	MB21	13.325	79.885	.985	-174.276	200.926
	MB23	-28.412	79.885	.933	-216.013	159.189
MB23	MB21	41.737	79.885	.860	-145.864	229.338
	MB22	28.412	79.885	.933	-159.189	216.013

Table A19. ANOVA tests of total costs for c_{it}=15, c_{ot}=22.5 and Mean 50 minutes

Dependent Variable: MB31						
Tukey HSD						
(I) Weights	(J) Weights	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
MB31	MB32	265.118	231.567	.487	-278.692	808.928
	MB33	67.810	231.567	.954	-476.000	611.620
MB32	MB31	-265.118	231.567	.487	-808.928	278.692
	MB33	-197.308	231.567	.671	-741.118	346.501
MB33	MB31	-67.810	231.567	.954	-611.620	476.000
	MB32	197.308	231.567	.671	-346.501	741.118

Table A20. ANOVA tests of total costs for for c_{it}=50, c_{ot}=75 and Mean 50 minutes

Label Mean=75minutes	Basic Model Mean3	NORA Model Option 2 Mean3	NORA Model Option 3 Mean3
c_{it}=1, c_{ot}=1.5	MC11	MC12	MC13
c_{it}=15, c_{ot}=22.5	MC21	MC22	MC23
c_{it}=50, c_{ot}=75	MC31	MC32	MC33

Table A21. Model labels for Table A22-A24

Dependent Variable: MC11						
Tukey HSD						
(I) Weights	(J) Weights	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
MC11	MC12	3.459	22.234	.987	-48.756	55.674
	MC13	-5.252	22.234	.970	-57.467	46.963
MC12	MC11	-3.459	22.234	.987	-55.674	48.756
	MC13	-8.712	22.234	.919	-60.926	43.503
MC13	MC11	5.252	22.234	.970	-46.963	57.467
	MC12	8.712	22.234	.919	-43.503	60.926

Table A22. ANOVA tests of total costs for for c_{it}=1, c_{ot}=1.5 and Mean 75 minutes

Dependent Variable: MC21						
Tukey HSD						
(I) Weights	(J) Weights	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
MC21	MC22	-70.674	115.092	.812	-340.955	199.607
	MC23	130.984	115.092	.491	-139.297	401.265
MC22	MC21	70.674	115.092	.812	-199.607	340.955
	MC23	201.658	115.092	.187	-68.623	471.939
MC23	MC21	-130.984	115.092	.491	-401.265	139.297
	MC22	-201.658	115.092	.187	-471.939	68.623

Table A22. ANOVA tests of total costs for for c_{it}=15, c_{ot}=22.5 and Mean 75 minutes

Dependent Variable: MC31						
Tukey HSD						
(I) Weights	(J) Weights	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
MC31	MC32	-52.808	330.429	.986	-828.785	723.169
	MC33	653.115	330.429	.119	-122.862	1429.091
MC32	MC31	52.808	330.429	.986	-723.169	828.785
	MC33	705.922	330.429	.083	-70.054	1481.899
MC33	MC31	-653.115	330.429	.119	-1429.091	122.862
	MC32	-705.922	330.429	.083	-1481.899	70.054

Table A24. ANOVA tests of total costs for for c_{it}=50, c_{ot}=75 and Mean 75 minutes