STOCHASTIC SCHEDULING OF OPERATING ROOMS AND REUSABLE MEDICAL DEVICES: A SIMULATION OPTIMIZATION APPROACH

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STOCHASTIC SCHEDULING OF OPERATING ROOMS AND REUSABLE MEDICAL DEVICES: A SIMULATION OPTIMIZATION APPROACH

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To my family

The greatest treasure is, was,

and always will be

ABSTRACT

Health care expenditures are expected to grow every year, and more than 40% of a hospital's total expenses and revenues are generated by surgical surgeries. One of the major resources required during surgeries are reusable medical devices (RMDs). RMDs are surgical instruments utilized during surgeries which have to be reprocessed by thorough cleaning followed by high-level disinfection or sterilization after each use. RMDs have to be planned with operating rooms (ORs) concurrently since insufficient RMDs may cause delays in surgery starting times. However, management of RMD sterilization stage is nontrivial. First, RMDs are sent to sterilization service at different times due to different finishing times of surgeries during a day. Second, the decision of how to load the sterilization machines, i.e., how to batch RMDs, is a complicated one. Lastly, time spent during sterilization has to be considered during scheduling of ORs since an surgery cannot start without the required number of RMDs. In this thesis, we study the integrated scheduling of ORs and sterilization of RMDs under stochastic surgery durations. We propose a simulation optimization approach to tackle with this problem, and through numerical studies show that our approach could lead to significant (15% on average) cost savings in compare to deterministic approaches for a hospital.

Keywords: Scheduling, Health Care, Simulation Optimization

ÖZETÇE

Sağlık hizmeti harcamalarının her yıl artması beklenmektedir. Hastanelerin harcama ve gelirlerinin 40%ı da ameliyatlar sonucunda oluşur. Ameliyatlar sırasında ihtiyaç duyulan en önemli kaynaklardan biri tekrar-kullanımlık tıbbi cihazlardır(reusable medical device, RMD). Ameliyatlar sırasında kullanılan RMD'ler, her işlem sonrasında detaylıca temizlenmek ve sonrasında da dezenfekte veya sterilize eldilmek zorundadır. RMD'lerin yetersizliği, ameliyatların başlama zamanlarının gecikmesine sebep olacağından RMD'lerin sterilizasyonu ameliyathanelerle eşzamanlı olarak planlanmalıdır. Ancak, RMD'lerin sterilizasyon aşamasının yönetimi kolay değildir. İlk olarak, gün boyunca farklı ameliyatlarda kullanıldıklarından, RMD'ler sterilizasyon servisine farklı zamanlarda gönderilir. İkinci olarak, sterilizasyon makinalarına RMD'lerin nasıl yükleneceği (ör. RMD'lerin nasıl gruplanacağı) kararı zor bir karardır. Son olarak da yeterli sayıda RMD olmadan ameliyata başlanamayacağından, sterilizasyonda harcanacak zaman ameliyathanelerin çizelgelenmesiyle birlikte dikkate alınmalıdır. Bu tezde, stokastik ameliyat süreleri altında ameliyathanelerin entegre planlanması ve RMD'lerin sterilizasyonu incelenmiştir. Bu problemin çözümü için bir simülasyon optimizasyon yaklaşımı önerilmiştir ve sayısal araştırmalar yoluyla yaklaşımımızın deterministik yaklaşımlarla karşılaştırıldığında bir hastane için önemli (ortalama 15%) maliyet tasarrufu sağlayabileceği gösterilmiştir.

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CHAPTER I

INTRODUCTION

Health care expenditures are expected to grow every year, and more than 40% of a hospital's total expenses and revenues are generated by surgical surgeries Erdogan and Denton (2011). By planning and scheduling of operating rooms (ORs) with improved efficiency and quality, healthcare service providers aim at decreasing the costs and maintaining the quality of patient care. However, in scheduling ORs, service providers always face impediments and because of that quality of scheduling decreases and lead to a decrease in revenue, a bad experience for patients and in some cases health problems for patients. For these reasons, ORs scheduling has become one of the important and productive research areas for researchers.

In the scheduling of operating rooms, researchers should consider different factors in their research. Factors like patient characteristics, performance measures, decision level, solution technique, and uncertainty (Cardoen et al. (2010)). Each of these factors is combined and become a new filed. Patient characteristics can be simply divided into elective (inpatient or outpatient) or non-elective (urgency or emergency). In performance measures, we discuss criteria like utilization, financial values or preferences. decision level focuses on what kind of decision we want to make like time, room, capacity or if our decision is acceptable for operating team or patient. Besides, solution techniques can differ based on our previous factors, such as using mathematical programming methods, simulation or constructive heuristics. Another important factor that has the most effect in the scheduling of ORs is uncertainty that can be implanted in the arrival of patients, duration of surgeries or in resources like surgeons, operating rooms or medical devices. Uncertainty has the most effect on selecting the solution techniques, stochastic approach or deterministic approach. In this thesis, we focused on uncertainty in the duration of surgeries and the availability of resources.

There are several approaches for scheduling of ORs. For example, scheduling surgeries with a smaller duration at the beginning of day and surgeries with a higher duration through the end of the day, or assigning special rooms for each department in the hospital. In some approaches, hospitals keep one of the operating rooms empty for non-elective (urgency or emergency) patients. The main factor affecting these decisions is the level of uncertainty and location of uncertainty(arrival, duration or resource). In this thesis, we considered the arrival of patients and resources as deterministic and only addressed the uncertainty in surgery duration.

Knowing the duration of surgeries in advance (deterministic case), can help the service providers to make a better decision, on the other hand, in the real world, the durations of surgeries have a stochastic behavior. An uncertain environment and in our case stochasticity in the duration of surgeries makes the scheduling of surgery difficult and reduces the quality of our decisions. For example, if an surgery finishes before its planned time, it leads to idle time in operating rooms and on the other hand, if the surgeries take more than its planned schedule, we will have overtime in operating rooms and higher waiting time for upcoming surgeries. It also can affect the availability of resources needed for upcoming surgeries.

During OR planning and scheduling, there are various required resources. One of the major resources required during surgeries is reusable medical devices (RMDs). RMDs are surgical instruments, such as, clamps, forceps, and endoscopes, utilized during surgical surgeries which have to be reprocessed by thorough cleaning followed by high-level disinfection or sterilization after each use. RMDs have to be planned with ORs concurrently since insufficient RMDs may cause delays in surgery starting times.

An extensive reprocessing of RMDs is required to prevent possible nosocomial infections (Ozturk et al., 2010) since one of the reasons for surgical site infections is the inadequate sterilization of surgical instruments (Spagnolo et al., 2013). Sterilization is a complicated process consisting of several stages. However, management of RMD sterilization stage is nontrivial. First, RMDs are sent to sterilization service at different times due to different starting times and finishing times of surgeries during a day (Ozturk et al., 2014). Second, the decision of how to load the sterilization machines, i.e., how to batch RMDs, is a complicated one. Lastly, the time spent during sterilization has to be considered during the scheduling of ORs since an surgery cannot start without the required number of RMDs.

While planning and scheduling ORs considering RMDs, inherent uncertainties in surgery durations cannot be ignored and create another challenge. Because the duration of surgeries is unknown in advance to surgery, we can not be sure that the sterilization schedule will be on time, and in some instances because the surgeries finish after the schedule of sterilization machine, dirty RMDs cannot be sterilized and it can lead to cancellation of upcoming surgery. To overcome these problems, several mathematical models have been introduced, but there is still a need for improvement and an extension that covers all aspects of operating room scheduling. To this aim, we developed a simulation optimization method to deal with uncertainty in the duration of surgeries and effective scheduling of sterilization machines to increase the efficiency and utilization of ORs.

The remainder of this study is organized as follows: Chapter 2 provides a brief review of the literature related to OR scheduling and Simulation methods. Chapter 3 presents the problem definition and presented solution approaches. Chapters 4 and 5 contain our data sets, numerical analysis, and extension. Chapter 6 concludes the thesis providing directions for future research.

CHAPTER II

LITERATURE REVIEW

We categorize the related work as OR scheduling, Simulation in Scheduling and Simulation Optimization in OR scheduling.

2.1 OR scheduling

ORs are considered as one of the most expensive resources in hospitals (Cardoen et al., 2009). Surgical sector expenses account approximately 33% of the projected hospital budget (Macario, 2006). Thus, hospital administration aims to utilize this costly resource efficiently and consequently OR planning and scheduling has been the focus for a large body of literature for the last half-century. For a more complete review of recent literature on operating room planning and scheduling we refer the works of Gupta and Denton (2008), Cardoen et al. (2010), Erdogan and Denton (2011), and Ahmadi-Javid et al. (2017). Cardoen et al. (2010) states that there are 247 papers published in this area during the past sixty years and categorize them along six dimensions related to modelling assumptions, solution methods, and implementation results. In this section, we will briefly review this vast literature with a particular focus on (i) deterministic approaches, (ii) stochastic problems, and (iii) simulation-optimization as the solution methodology.

A major concern of OR planning and scheduling problems is to find when and at which operating room surgery will start for a given short planning horizon and a set of surgeries. The papers that attempt to solve this problem while ignoring any uncertainty tend to model the problem as a job shop scheduling extension called multi-mode blocking job shop. Practical sized instances are solved by the proposed mixed-integer linear program (Pham and Klinkert, 2008). A three-phase approach considering overtime, throughput, and the waiting list is studied by Testi et al. (2007). Another study assigning OR blocks to surgeons minimizing the shortfalls between a surgical group's target and actual assignment is explained by Blake et al. (2002). A master surgical schedule is generated by an integer programming model for a real-life hospital (Blake and Donald, 2002). In addition, a weekly OR scheduling problem maximizing the utilization of ORs and minimizing the overtime of ORs and the unexpected idle time between surgeries is modelled as a set-partitioning integer-programming model and solved by a column-generation-based heuristic procedure (Fei et al., 2010).

Various performance measures are defined in the literature to evaluate the quality of the OR schedule. Main ones can be summarized as waiting time, throughput, utilization, levelling, makespan, surgery cancellations, financial measures and preferences (Cardoen et al., 2009). Makespan, the completion time of the last patient's recovery, is minimized in the works of Marcon and Dexter (2006). Decreasing the makespan often results in a dense schedule. OR staffing costs are minimized by Dexter et al. (2000). A multiple objective surgical case scheduling problem is solved by both exact and heuristic algorithms based on integer programming and branch-and-bound in Cardoen et al. (2009). The authors prove that this optimization problem is NP-Hard. Additionally, solving the deterministic OR scheduling problem with identical waiting and overtime costs is shown to be strongly NP-hard (Kong et al., 2016).

In addition, other important surgical resources, such as surgical nurses, medical devices, are also considered during OR planning and scheduling problems since mishandling these resources may hinder efficiency, such as delaying surgery starting times. Nonrenewable resources are checked whether the aggregate demand of such resources is satisfied throughout the time horizon (Meskens et al., 2013), whereas, renewable resources have to be scheduled similarly to ORs. Wang et al. (2015); Xiang et al. (2015) integrate multiple nurse roster constraints into OR scheduling problem and solve the problem using ant colony optimization. Guo et al. (2016) formulates an integrated elective surgeries and surgical nurses scheduling problem and uses a genetic algorithm to solve the resulting integer programming model. Similarly, Rath et al. (2017) studies integrated anesthesiologist and OR scheduling problem.

Workforce resources like nurses or anesthesiologists are usually assumed to be available just after the surgery finishes in the works mentioned above. RMDs are another type of renewable resources utilized during OR scheduling, and unlike nurses' or anesthesiologists' rescheduling during a day, RMDs cannot be reused immediately when the surgery is over. Coban (2018) shows that integrating OR planning and scheduling problem and RMD sterilization scheduling problem improves the performance of OR and decreases total costs. van de Klundert et al. (2008) study sterilization logistics in hospitals while minimizing the total cost, the sum of transportation cost linear in the number of transports to OR, OR storage cost linear in storage space the instruments (RMDs) contain, and sterile equipment cost linear in the number of times the equipment is used. Standardization of net decomposition, a pile of instruments sorted in pouches, and pull logistics for a limited set of surgery types are shown to result in over $500,000$ Euro in annual savings. Ozturk et al. (2010) study washing surgeries of RMDs to minimize makespan when RMD nets have different release times and different sizes. They model this problem by a mixed-integer linear programming model and develop heuristics based on classical bin packing algorithms. A branch-and-bound based heuristic is proposed for the same problem studied by Ozturk et al. (2010) but larger instances (up to 40 jobs) can be solved (Ozturk et al., 2014).

Inherent uncertainties in surgery durations create another challenge for solving OR scheduling problems. Most of the papers in this stream consider a single OR, whereas there are a few recent papers that model multiple ORs (see, for example, Batun et al. (2011) and Gul et al. (2015)). Weiss (1990) is the first paper that formulates the optimal scheduling problem and offers "newsvendor-type" critical fractile solution as a heuristic. Efficient computations of optimal solutions under specific continuous distributions (Wang (1993), Wang (1997)) and discrete distributions (Begen and Queyranne (2011)) are proposed for single OR problems as well. Denton and Gupta (2003) study the single server appointment scheduling problem to determine optimum starting times for each surgery. They model the problem as a two-stage stochastic linear program. Since the exact solution is not possible beyond three surgeries, various heuristics are suggested in the literature (Robinson and Chen (2003), Khaniyev et al. (2018)).

From a practical viewpoint, it is critical to solving sequencing and scheduling problems simultaneously. However, this problem is extremely difficult: Solving the stochastic version of this problem using the sample average approximation method is NP-complete (Mancilla and Storer (2012)). Hence, papers in this stream either develop and/or analyze heuristics (such as sequencing surgeries in order of increasing variation (SVF)). Denton et al. (2007) simultaneously study the effect of sequencing and scheduling start times of surgeries. They formulate a two-stage stochastic mixed-integer programming model and find that sequencing surgery in order of increasing variance is optimal under certain cases. Mancilla and Storer (2012) considers the similar problem. They argue that as the number of scenarios used in the sample average approximation method increases, the difference between the optimality gaps of SVF rule and using the more advanced Benders-based heuristics decreases when costs are identical between surgeries. Under certain cases, other sequencing rules could provide better performance (see Kong et al. (2016) for cases where SVF is suboptimal, Mak et al. (2014b) for another sequencing heuristic, ordering by increasing order of variance to waiting cost ratio).

2.2 *Simulation in Scheduling*

Apart from the stochastic optimization methodology, simulation-based approaches are also proposed in the literature as an effective way to deal with uncertainty. Lu Zhen (2014) suggested a simulation optimization method to solve ambulance deployment and relocation problems using genetic algorithm under the arrival of service calls and service times are random. Safa Bhar Layeb (2018) studied the use of Simulation Optimization Model to find optimal services schedule ina real-world case study for stochastic multimodal freight transportation systems. Lien Vanbrabant (2019) did a comprehensive review on the use of simulation methods in healthcare and use of Key performance indicators as a performance measurement. Min and Yih (2010) proposed a sample average approximation method to solve a model with uncertainties in surgery duration and available resources. Molina-Pariente et al. (2018) suggested solving the scheduling problem by combing the greedy local search method and Monte Carlo simulation. They considered uncertainty in the duration of surgeries and arrival of emergency patients with an objective to minimize the undertime and overtime costs of ORs and the cost of exceeding the capacity constraints of the system. Saremi et al. (2013) considered limited availability of multiple resources to minimize the waiting time of the patients, compilation time of surgeries and number of cancellations by introducing simulation-based Tabu search and integer programming enhanced tabu search. Patients are categorized into different types, where each type has different stochastic service time.

Lamiri et al. (2008) suggested a Monte Carlo optimization method combining Monte Carlo simulation and mixed-integer programming to minimize the sum of surgery cost and operating room overtime costs where both elective and non-elective patients exist. In addition, according to Jorge Haddock (1992) simulation annealing can be used as a simulation optimization method to find optimal or near-optimal solutions. Rym M'Hallah (2019) used Sample average approximation to approximately solve the stochastic integer model of scheduling elective surgeries where the uncertainty is in surgery times, intensive care unit times and post-surgery lengths of stays. Jorge Haddock (1992) integrated SAA method with robust linear programming to select and schedule next–day surgeries from list of candidate patients with consideration of stochastic surgery duration, and they reported that their suggested method's competition time is approximately one-quarter of that of SAA. Baesler et al. (2015) offered a simulated annealing algorithm connected to the simulation model to solve stochastic operating room scheduling problem, which is found to improve hospital schedule by 18%.

2.3 Simulation Optimization in OR scheduling

Satyajith Amaran (2016) did a review of algorithms and applications of simulation optimization and divided application of SO to discrete-event simulations and stochastic differential equation system. Ping-Shun Chen and Che (2015) solved the appointment scheduling problem with stochastic patient treatment time using SO algorithm. Their objective was to minimize the expected value of doctors total idle time and patients total waiting time.

Several papers tried to solve both the scheduling and sequencing of surgeries simultaneously with simulation-optimization based solutions. Landa et al. (2016) divided the problem into two sub problems to increase OR utilization and decrease the number of cancelled surgeries. First, they assigned each surgery to a day and room, then they decide in which sequence the surgeries will be done under stochastic surgery durations. For this propose they develop a hybrid two-phase optimization algorithm by combining Monte Carlo simulation and neighbourhood search techniques. Saadouli et al. (2015) aimed to minimize the makespan of operating rooms in two phases considering both ORs and recovery beds where surgery duration is uncertain. They propose a knapsack model to select surgeries for a day coupled with an integer programming model to assign surgeries to different rooms. Then a discrete event simulation model was suggested to evaluate the solutions.

To the best of our knowledge, integrated scheduling of ORs and sterilization of RMDs under stochastic surgery durations has not been studied in the literature. This thesis fills that gap in this research problem and offers simulation-optimization as a solution technique.

CHAPTER III

PROBLEM DEFINITION AND SOLUTION APPROACHES

3.1 Problem Definition

In the traditional scheduling of ORs, hospital management and relevant hospital staff construct the operating table (OT) for upcoming surgeries. OT contains the sequence and schedule of surgeries and the schedule of the sterilization machine. OT aims to satisfy certain criteria: minimizing the idle time of ORs, decreasing the closing time and overtime of ORs, reduce the number of the possible cancellation of surgeries and decrease costs related to sterilization of RMDs. Management constructs the OT based on their previous experiment of the duration of each surgery, after that, they create a schedule for the sterilization machine to support clean RMD requirements of each surgery. In each period, based on sequence and schedule of each surgery if the number of available clean RMD met the requirement of that surgery, the surgery begins, otherwise, they postpone the surgery until RMD requirements are met or they may cancel the surgery. In this thesis, we made the following assumptions:

- Surgery duration is uncertain and following the log-normal distribution
- Only one sterilization machine is available
- All RMDs at the beginning of the day are clean
- Different types of Surgeries can be done in any of the rooms
- There is no need to clean RMDs at the end of the day
- All Surgeries are elective and there is no out-patient

- Only next day's Surgery is scheduled
- Surgeries are different by the number of their RMD requirement and process time
- There is no cancellation in the time of scheduling
- Number of RMD requirements and distribution of surgery duration are known in advance

In this Chapter, we present a simulation optimization approach to determine the optimal surgery duration by minimizing the costs of key performance indicator (KPI). In our approach, we assumed that the quality of our solution can be measured by KPI. For the deterministic model, this quality is being measured by weighted sum of using sterilization machines, sterilization of each RMD (α_1), OR idle time (α_2), and makespan of surgeries (α_3). In the simulation stage of our approach, KPI is the weighted sum of costs related to sterilization (unit cost of 150), idle time (unit cost of 10), over time (unit cost of 10) and number of cancellation (unit cost of 50,150).

3.2 Simulation Optimization Approach

As we mentioned in Chapter 1 it is important to schedule the ORs considering the availability of other resources and uncertainty in surgery duration. For this purpose, we developed a simulation optimization algorithm given a set of surgeries, schedules the ORs based on presuming duration of surgeries and their RMD requirements. In the proposed approach, ORs and sterilization machines are scheduled simultaneously to decrease the over time, idle time of operating rooms and cancellations of surgeries related to unavailability of RMDs. After constructing the operating table, to overcome the uncertainty in surgery duration, our approach simulates the schedule with different scenarios related to the possible duration of surgeries and calculates the KPIs related to the current schedule. By repeating this process, we determine the best duration for each surgery to schedule the ORs, knowing uncertainty will have the least effect on this schedule. The flow chart of the proposed solution approach is represented in Figure-1.

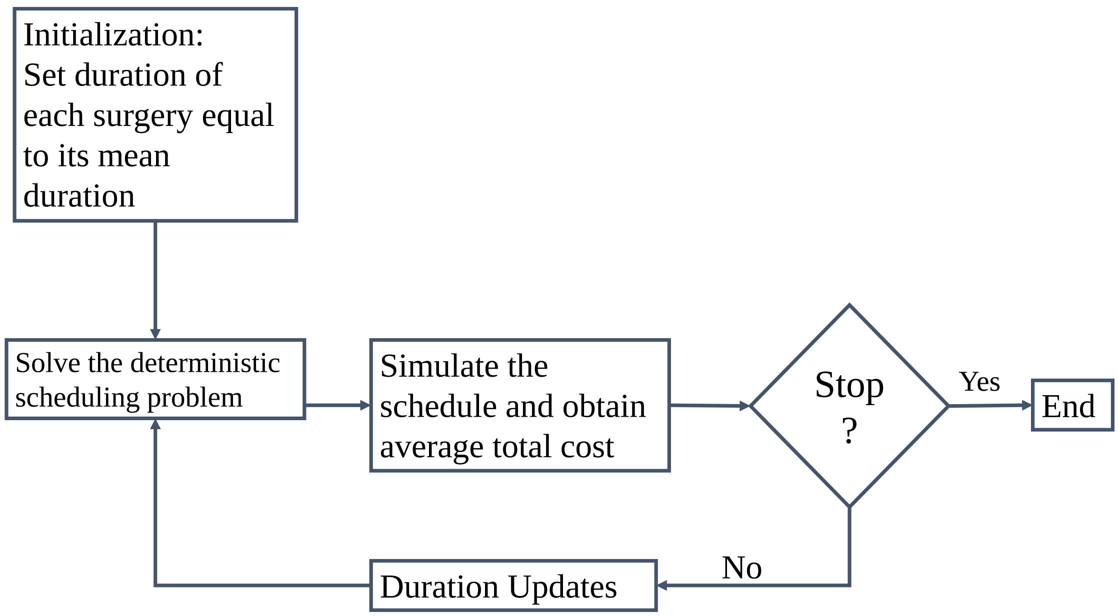

Figure 1: Flowchart of the proposed simulation optimization approach.

3.2.1 Deterministic Model

We model the integrated scheduling problem of OR and sterilization of RMDs by an integer linear programming model. All information required about the surgeries, including the duration of each surgery, is given before scheduling, however, surgery durations may vary due to uncertainty prevalent during surgeries. Transfer times of RMDs between OR and sterilization services are assumed to be negligible. Once the surgery starts, it cannot be interrupted. Lastly, we assume that all surgeries require the same type of RMDs, but required numbers of RMDs vary concerning surgeries.

Table 1: Nomenclature

Indices	
o	surgery, $o \in O$
t	Time, $t \in T$
r	Operating room, $r \in R$
Parameters	
n_o	number of RMDs required for each surgery o
p_o	duration of each surgery o
$ster$	time required for sterilization of one batch of RMDs
cap	capacity of sterilization machine
$mach$	number of sterilization machines
$cost_{ster}$	cost of sterilizing a RMD for one time unit
$cost_{mach}$	cost of using sterilization machine for one time unit
α_i	weights used in objective function, $i \in \{1, 2, 3\}$
c_0	number of clean RMDs at time 0
d_0	number of dirty RMDs at time 0
Decision Variables	
$x_{o,t,r}$	1 if surgery o starts at time t at operating room r; 0 otherwise
i_r	idle time of operating room r
e_r	makespan of operating room r
c_t	number of clean RMDs at the beginning of time t
d_t	number of dirty RMDs at the beginning of time t
s_t	number of RMDs that starts to be sterilized at the beginning of time t
m_t	number of sterilization machines that starts sterilization at the beginning of time t
M	makespan

$$\min \sum_{t} \alpha_1(cost_{mach} m_t + cost_{ster} s_t) + \alpha_2 \sum_{r} i_r + \alpha_3 M$$

$$\text{s.t.} \quad c_{t-1} - \sum_{r \in R} \sum_{o \in O} n_o x_{o,t,r} + s_{t-ster} = c_t \;\; \forall t \in T, t \geq 1 + ster \tag{1}$$

$$c_{t-1} - \sum_{r \in R} \sum_{o \in O} n_o x_{o,t,r} = c_t \quad \forall t \in T, t \leq ster \tag{2}$$

$$d_{t-1} - s_t + \sum_{r \in R} \sum_{o \in O: t-p_o \geq 1} n_o x_{o,t,r} = d_t \quad \forall t \in T \tag{3}$$

$$s_t \leq cap\, m_t \quad \forall t \in T \tag{4}$$

$$\sum_{\bar{t}=t-ster}^{t-1} m_{\bar{t}} \leq mach \quad \forall t \in T : t \geq ster \tag{5}$$

$$\sum_{o \in O} \sum_{\bar{t} \in \bar{T}: t-p_o \geq 1} x_{o,\bar{t},r} \leq 1 \quad \forall r \in R, t \in T, \bar{T} = \{t - p_o, .., t-1\} \tag{6}$$

$$\sum_{t \in T} \sum_{r \in R} x_{o,t,r} = 1 \quad \forall o \in O \tag{7}$$

$$e_r \geq \sum_{t \in T} (t + p_o) x_{o,t,r} \quad \forall o \in O, r \in R \tag{8}$$

$$M \geq e_r \quad \forall r \in R \tag{9}$$

$$i_r \geq e_r - \sum_{o \in O, t \in T} p_o \, x_{o,t,r} \quad r \in R \tag{10}$$

$$x_{o,t,r} \in \{0, 1\} \quad \forall o \in O, t \in T, r \in R \tag{11}$$

$$M \geq 0 \text{ and } e_r, i_r \geq 0 \quad \forall r \in R \tag{12}$$

$$c_t, d_t, s_t, m_t \geq 0 \text{ and } integer \quad \forall t \in T \tag{13}$$

The objective function is to minimize the total cost, which comprises using sterilization machines, sterilizing each RMD, OR idle time, and makespan of surgeries. The first and the second constraints are inventory balance equations for clean RMDs, whereas, dirty RMDs' inventory balance equation is satisfied by constraint (3). Capacity of sterilization machines is satisfied by constraint (4). Constraint (5) ensures that total number of busy sterilization machines at every time period is less than or equal to the number of sterilization machines. Constraint (6) guarantees at most one surgery can be processed at an OR at a given time, and constraint (7) ensures that every surgery should be processed. Constraints (8), (9), and (10) define the makespan of each operating room, the makespan, and the OR idle time, respectively. Lastly, non-negativity and binary variables are stated by constraints (11)-(13) (α_1 is 0.1 and for α_2 and α_3 the value of 10 is selected).

3.2.2 Simulation

In the proposed simulation-optimization procedure, we first solve the mathematical model introduced in Section 3.2.1 developed for integrated scheduling of ORs and sterilization of RMDs. Then, we evaluate the performance of the solution computed by the mathematical model under uncertain surgery duration. The pseudocode of our proposed aproach is shown in Algorithm 1 and the steps of algorithm is as follow:

1. First, Set the duration of surgeries equal to the mean of duration, the standard deviation is also equal to the standard deviation of surgeries
2. Solve the deterministic model
3. Extract the sequence of surgeries and schedule of the sterilization machine from the deterministic solution
4. Generate scenarios based on mean and standard deviation of each surgery using log-normal distribution
5. Using the sequence of surgeries and schedule of machine simulate the solution
6. Calculate the KPIs
7. Update the best KPI if needed
8. Increase/Decrease the duration of all the surgeries at the same time, return to step 2, if no improved KPI found, go to step 9
9. For each operation, update its duration to mean + 2*SD, return to step 2

10. Reduce the duration of the surgery by 1 in each iteration

11. Stop if duration of all surguries are updated in step 9, else move to next operation

Predicting and generating the duration of surgeries are an important part of any simulation approach. Base on Strum et al. (2003), we assumed that the duration of surgeries is following the log-normal distribution. In addition, in this thesis, sterilization itself has several stages and different costs. For the sake of simplicity, we considered all the stages of sterilization as one stage. In addition, we divided the costs related to sterilization into fixed cost of using the sterilization machine, and variable cost of sterilizing of each RMD.

We assumed two conditions for cancelling a surgery: 1. no surgery can start after the closing time of the OR, or, 2. If the number of clean RMDs is less than the requirement of surgery and there is no schedule for sterilization machine in upcoming periods. We also assigned a cost to OR's overtime and idle time in which by minimizing these costs we can increase the utilization of ORs. As shown in Figure 70, overtime happens by keeping the ORs open after its scheduled closing time and idle time is the periods that ORs are open but not being used for surgery.

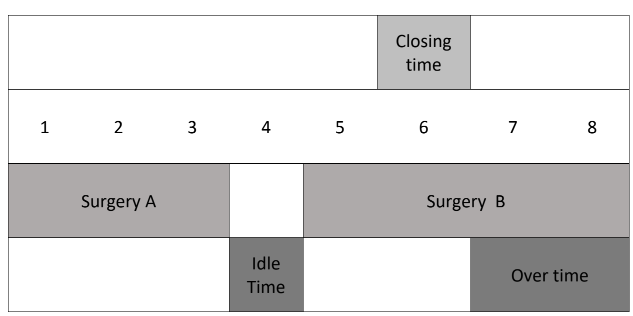

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Figure 2: Idle time and Over time

Algorithm 1: Our proposed simulation optimization approach

Step 0: Initialize $KPI_{best} = M$, $O_s = O$, and $O_c = \{\}$, $iteration = 1$
p_o:= duration of surgery o used while solving the deterministic mathematical model introduced in Section 3.2.1
Step 1: Solve the deterministic mathematical model and compute KPI_d
$\overline{S}$:= Set of surgeries sequenced according to ascending starting times
$\overline{S_{sm}}$:= Staring times of working sterilization machines
Generate K scenarios for surgeries' durations
Step 2: Simulation
for *s=1:1:K* **do**
  p_o^s:= duration of surgery o in scenario s
  t= 1; initialize c_t, d_t, and s_t
  while $t \leq T$ **do**
    if *sterilization machine works at time t according to* $\overline{S_{sm}}$ **then**
      if $d_t > 0$ **then**
        Start sterilization and update d_t, s_t, and $c_{t+ster-1}$
      end
    end
    if *there is an available OR* **then**
      Pick the first surgery o from $\overline{S}$
      if $c_t \geq n_o$ **then**
        Start surgery o, update c_t and d_{t+p_o-1}
        $\overline{S} = \overline{S} \setminus \{o\}$
      end
    end
    Update t := t +1
    if $\overline{S} = \emptyset$ **then**
      break
    end
  end
  if $\overline{S} \neq \emptyset$ **then**
    Cancel all remaining surgeries in $\overline{S}$
  end
  Compute KPI_s
end
Compute $\overline{KPI_{ave}}$
Set $KPI_{best} = \min\left\{\overline{KPI_{ave}}, KPI_{best}\right\}$
Step 3: Performance Comparison
while $p_o \neq 1 \, \forall o$ *and* $iteration = 1$ **do**
  Set $p_o = p_o \pm 1$, $\forall o$
  Repeat Steps 1 and 2
  if $KPI_{ave} < KPI_{best}$ **then**
    Update $KPI_{best} = KPI_{ave}$
  else
    break
    $iteration = iteration + 1$
  end
end

CHAPTER IV

COMPUTATIONAL RESULTS

To assess the performance of the proposed SO approach, a series of numerical experiments is performed. In section 4.1, we describe the generation of data sets used in numerical experiments. In section 4.2, the SO algorithm is tested on 16 types of problem instances. Results are compared with the solutions of the initial iteration. All algorithms are implemented in Java. To solve the deterministic formulation, ILOG Cplex 12.7 is used with a runtime limit of 2 minutes. Cplex and Java are run on a machine with Intel Core i7-8559U CPU @ 1.80 GHz processor and 8 GB RAM.

4.1 Data Generation

In order to test the proposed simulation optimization approach, a total of 432 instances are generated. The instances differ in the number of the operating room, initial available clean RMDs, RMD requirement of surgeries, cost of cancellation and standard deviation in the duration of each surgery in simulation. The number of ORs varies between 1 and 3. We study two cases for RMD requirement: (i) identical RMD requirement for all surgeries (2 RMDs per surgery), and (ii) different RMD requirement where required number of RMDs are generated randomly from the set $\{1, 2, 3, 4\}$. In addition, we studied two case for the initial number of available RMD, Scarce (40% of the average total required RMDs) and ample (80% of the average total required RMDs). The cost of cancellation is selected from the set $\{50, 150\}$. We also consider 1 hour to be equal to 4 periods in our instances. First, we assumed that the surgery durations are identified with mean 1 hour (4 time periods) and standard deviation 30 minutes (2 time periods), and then with mean of 1 hour and standard deviation randomly generated from $\{15, 30, 45\}$ minutes. For cases with heterogeneous

Table 2: Percentage KPI improvement for varying ORs.

Case	# of Instance	Duration	Initial RMD	Cancellation Cost	RMD need	# of ORs 1	2	3
1	1	4,2	Scarce	50	2	7.51%	4.23%	11.09%
2	5	4,random	Scarce	50	2	14.28%	8.94%	12.44%
3	1	4,2	Scarce	150	2	2.39%	4.67%	7.58%
4	5	4,random	Scarce	150	2	4.16%	6.61%	8.11%
5	1	4,2	Ample	50	2	41.92%	15.49%	13.59%
6	5	4,random	Ample	50	2	47.53%	18.05%	13.56%
7	1	4,2	Ample	150	2	8.80%	2.93%	4.07%
8	5	4,random	Ample	150	2	8.18%	6.45%	4.82%
9	5	4,2	Scarce	50	diverse	16.77%	19.41%	8.12%
10	25	4,random	Scarce	50	diverse	16.96%	18.84%	8.61%
11	5	4,2	Scarce	150	diverse	5.76%	8.46%	4.12%
12	25	4,random	Scarce	150	diverse	7.31%	9.61%	4.96%
13	5	4,2	Ample	50	diverse	47.26%	12.88%	8.30%
14	25	4,random	Ample	50	diverse	50.78%	17.37%	8.32%
15	5	4,2	Ample	150	diverse	12.76%	8.95%	15.39%
16	25	4,random	Ample	150	diverse	12.87%	9.79%	15.52%
Average						21.12%	12.95%	9.43%

duration, for each case, a total of 5 instances with different standard deviations are generated, and for the ones with different RMD requirement, for each case, 5 instances with different RMD requirements are generated considering the average number of RMD's to be 2.

All RMDs are assumed to be clean at the beginning of the day, and there is only one sterilization machine with a capacity of 8 RMDs and sterilization duration of 2 hours (8 time periods). The number of surgeries per OR is 5. In the case of the cost related to sterilization, a fixed cost of 150 is set for each time the machine works and a cost of 15 for each RMD in the machine. For idle time and overtime, the cost of 10 unit is considered for each period the system is idle or doing overtime.

4.2 Numerical Analysis

We generate a total of 432 instances as introduced in 4.1. Key performance indicator (KPI) is defined as the total cost of RMD sterilization (including sterilization machine cost), idle time, overtime, and cancellation. After the mathematical model introduced in Section 3.2.1 is solved, 10,000 samples are simulated given the sequence of surgeries and the schedule of sterilization machines computed by the mathematical model. Before updating the duration of surgeries that are given as input to the mathematical model, we record the KPI of this first iteration as *initial KPI* value. Then, durations are updated in the next iteration and the steps are repeated as introduced in Algorithm 1 unless a stopping criterion is met. The best value obtained during the iterations is recorded as the *best KPI* value. Percentage KPI improvement is defined as *(best KPI value - initial KPI value)/ initial KPI value*. The results are shown in Table 2.

Table 2 shows the average percentage KPI improvement for varying ORs. By not using the mean of surgury duration for scheduling the ORs, KPI improvement percentage increases for all of the instances. This shows us that the state-of-the-art approach usually utilized in the literature, using the mean values for surgery durations, may perform poorly. Thus, one should search for better initial durations instead of using the mean values, while solving the deterministic mathematical model

For the purpose of comparison of parameter's effect on total KPI, we used R software to construct a decision tree. We compared the KPI improvement percentage based on the number of ORs, initial RMDs, cost of cancellation and RMD requirements of surgeries. The result is shown in Figure 3. From the decision tree, we observe that on average we have 15% improvement, and if we divide the instances to 2 group of cases with cancellation cost of 50 and 150, we can see that in instances with lower cancellation cost the average KPI improvement is 20%, however, with higher cancellation cost, average KPI improvement decreases to 9.3%. Based on the decision tree, cancellation cost has the highest effect on the KPI, followed by the number of initial RMD and ORs.

In the case of cancellation cost, it has the most significant effect on KPI improvement. By tripling the cancellation cost, both the deterministic mathematical model and our simulation optimization approach decrease the number of surgery cancellations and it is shown in Figure 4. However, the KPI improvement percentage decreased from 20% to 9.3%. The reason for this is that by increasing the cancellation cost to 150, it becomes the highest cost in our model and to reduce its effect on the total KPI, our simulation optimization approach increases the operating room's make-span by increasing the duration of surgeries to postpone the closing period of operating rooms to avoid cancellation, and this increase will lead to higher total KPI and lower improvement. To do that, the SO approach schedules the sterilization machine after the arrival of the second dirty patch of RMDs to make sure of not missing the schedule of the machine and having clean RMDs for all surgeries, and this comes with the increase of make-span of operating rooms. In state of the art approach, on the other hand, the objective of minimizing idle time and overtime of operating rooms, and in addition, the constraint that pushes the model to do all surgeries, does not consider the uncertain nature of surgery durations.

As the initial RMD becomes ample from scarce and cancellation cost is 50, percentage KPI improvement increases up to 50 percent, however, by tripling the cancellation cost when the initial RMD is ample, KPI improvement reduces. The effect of

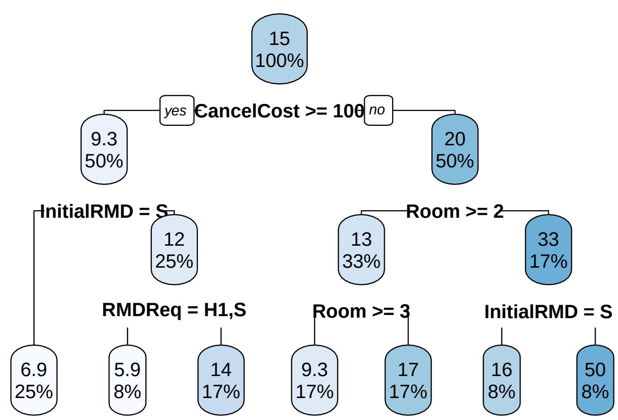

Figure 3: Comparison decision tree of KPI improvement

the number of initial RMDs shows us that the state of art approach cannot utilize ample RMDs correctly. In instances with ample RMD, the state of art approach schedule the sterilization machine to start after the first batch of dirty RMDs arrive, however, if the duration of surgeries takes longer than expected, it will miss the sterilization schedule or having less dirty RMDs in the machine than expected. By missing the schedule of sterilization the upcoming surgeries will not have enough clean RMDs to start. However, the SO approach postpones the schedule of the sterilization machine to avoid this problem. This will affect the make-span of operating rooms and increase the idle time, but on the other hand, it guarantees the sterilization of all dirty RMDs and the hospital will not miss the schedule of the machine.

Another factor in percentage improvement of KPI is the number of operating rooms. Increasing the number of ORs comes with the increase inthe number of surgeries and higher uncertainty in the model. Poor scheduling of surgeries or sterilization machines can lead to higher KPI in case of idle time, overtime or cancellation. The reason for that is the objective of deterministic model is to minimize all the costs, but

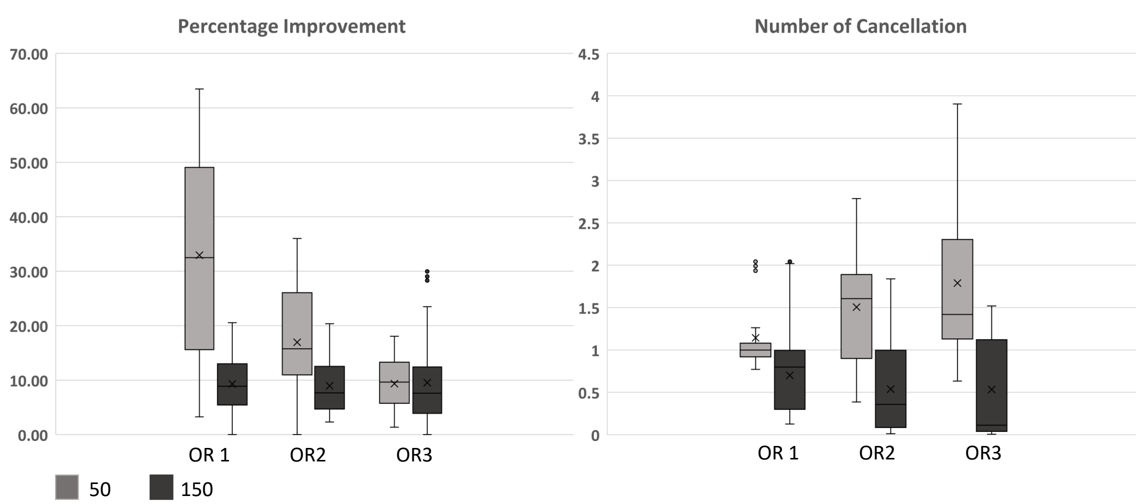

Figure 4: Effect of cancellation cost on KPI improvement and number of cancellation in cases with different number of ORs

in order to do that it cannot consider the effect of uncertainty in durations and as we discussed before missing the sterilization schedule will increases the total KPI. In our experiments, in instances with 1 OR, the KPI improvement is 21 percent, however increasing the number of OR's, decreases the improvement by half. This effect is more critical in instances with low cancellation cost, in which increase in the number of ORs, decreases the KPI improvement from 33 to 9.3 percent.

RMD requirements per surgery may vary in real life. However, due to nonexistent real data about exact RMD usage during surgeries, we capture varying RMD requirements of surgeries by generating RMD requirements not only as the same for all surgeries but also differing a cross surgeries. When the RMD requirement per surgery is the same, the percentage KPI improvement is at most 55%, however, when the RMD requirement per surgery varies, the percentage KPI improvement goes up to 89%. This shows that as RMD requirements vary, integrated scheduling of ORs and RMDs becomes a more vital task as one can benefit more from diverse RMD requirements while scheduling surgeries. For instance, instead of scheduling surgery A requiring 2 RMD sets, one may prefer to schedule both surgery B and C both requiring 1 RMD set or vice versa.

Another outcome is related to the optimality GAP and computational time of the cases. For solving the deterministic model, 2 minutes time limit is set for Cplex. In cases with 1 operating room, the algorithm found the optimal solution, however, for cases with more than 1 operating room, only in cases with ample initial RMD the algorithm found optimal or near-optimal solutions. Besides, by increasing the number of operating rooms, the combinational time increases significantly. On the other hand, the increase in the number of initial RMD decreases the computational time by half. Furthermore, we run the algorithm with an increase in the time limit for Cplex (3 minutes). There was an improvement in optimality Gap, but it did not affect the best solution KPI. The results are shown in Table 3

Table 3: CPU time of instances and average GAP percentage

	1 OR		2 OR		3 OR	
Instance	CPU Time (min)	GAP	CPU Time (min)	GAP	CPU Time (min)	GAP
1	1.92	0 %	31.41	29.16 %	240.89	61.42 %
2	2.72	0 %	49.64	20.38 %	251.21	41.12 %
3	2.61	0 %	32.50	51.8 %	241.90	72.01 %
4	2.79	0 %	46.32	37.4 %	249.62	70.16 %
5	0.77	0 %	19.91	0 %	141.99	0 %
6	0.89	0 %	20.91	0 %	140.80	0 %
7	0.81	0 %	19.44	0 %	139.42	0 %
8	0.86	0 %	22.45	0 %	141.83	0.47 %
9	1.79	0 %	72.22	27.03 %	254.23	42.32 %
10	1.77	0 %	62.44	22.62 %	254.20	46.18 %
11	2.00	0 %	78.51	32.95 %	240.90	21.98 %
12	1.90	0 %	67.55	35.19 %	252.42	28.77 %
13	0.82	0 %	21.49	0 %	140.42	0 %
14	0.85	0 %	22.05	0 %	140.55	3.62 %
15	0.82	0 %	23.30	0 %	141.92	0.7 %
16	0.81	0 %	22.88	0 %	141.92	0 %

CHAPTER V

EXTENSION: DYNAMIC RESCHEDULING

5.1 Model development

For solution approach, we proposed a simulation optimization framework in which beside the sequence and schedule of surgeries, we take the schedule of sterilization machine from deterministic model and simulate the instance to find KPI of this instance. However, in some of the hospitals, the management may prefer to have a more dynamic schedule for surgeries or sterilization machine. To meet this demand, we considered 2 extensions that finds the optimal surgery and sterilization schedule in a dynamic environment. In section 5.1.1, we explain dynamic rescheduling of surgeries, section 5.1.2 is related to dynamic rescheduling of the sterilization machine. finally, in section 5.2 we will compare the quality of results of these approaches and the main approach and discuss when each approach should be used.

5.1.1 Dynamic Rescheduling Of Surgeries

In the main approach, the deterministic model gives us the sequence of surgeries and in addition the assignment of surgeries to ORs. However, even if a surgery finishes before its schedule (due to uncertainty in surgery duration) and OR becomes idle, we cannot start another surgery if the surgery is not assigned to that room. To test the effect of this assumption on our approach, we suggest an alternative assignment system in which the assignment of surgeries could be changed during the day (in our approach, in the simulation stage). All the stages of the main approach are applied except using the assignment found in the deterministic model. In dynamic rescheduling of surgeries (DRR), the assignment of surgeries to ORs could be changed in each period by checking the availability and remaining capacity of each OR. This approach aims to decrease the idle time of operating rooms considering the fact that we assumed that OR's can support any type of surgeries. The steps of dynamic rescheduling of surgeries are as follow:

Algorithm 2: Dynamic Rescheduling Of Surgeries

```
for each period do
    if have empty room or an surgery is done then
        for each room do
            if room is empty then
                Availability = closing period  current period
            end
            if room is in use then
                Availability = closing time - expected finishing of current surgery
                if passed the expected finishing time then
                    Availability = closing period  next period
                end
            end
        end
    end
    Sort availability of rooms in non-decreasing order
    Find expected surgery assignment
    if room with highest availability is empty then
        Start assigning surgeries to ORs from highest in decreasing order
    end
    if room with highest availability is currently busy then
        Move to next OR with highest availability and assign
    end
end
```

5.1.2 Dynamic Rescheduling Of Sterilization Machines

In dynamic rescheduling of sterilization machines (DRSM) approach, the schedule of sterilization machine is based on the number of dirty RMDs at each period. For this approach we calculate a threshold in each period and if the criteria is satisfied, we start the sterilization process. Threshold itself can be calculated with two methods . In the first method, threshold criteria depends on cancellation cost of surgeries, the algorithm is as follow:

Algorithm 3: Dynamic Rescheduling Of Sterilization Machines, method 1

d_t: number of dirty RMDs at time t
n: number of RMDs
for *each period* **do**
    if *cancellation cost is less than 100* **then**
        if $\frac{d_t}{n} < 0.8$ **then**
            Start the sterilization machine
        else
            Move to next period
        end
    end
    if *cancellation cost is higher than 100* **then**
        if $\frac{d_t}{n} < 0.5$ **then**
            Start the sterilization machine
        else
            Move to next period
        end
    end
end

For the second method, we first introduce the following parameters:

l_t: number of remaining surgeries in period t

K: sterilization machine fixed cost

k: variable cost of a unit RMD in sterilization machine

$Idle$: cost of an operating room being idle for one period of time

Du: expected duration of an surgery

R: RMD requirement of an surgery

C: cancellation cost of a surgery

And the algorithm is as follow:

Algorithm 4: Dynamic Rescheduling Of Sterilization Machines, method 2

for *each period* **do**
    Calculate total sterilization cost for rest of the surgeries
    Calculate cancellation and idle time cost for the rest of the surgeries
    if $\frac{K+(k*R*l_t)}{(l_t*C)+(l_t*Idle*Du)} < 1$ **then**
        Start the sterilization machine
    else
        Move to next period
    end
end

5.2 Computational Analysis

To see the effect of dynamic rescheduling approaches, we test the approaches with the data set in Chapter 4.1. The results for dynamic rescheduling of sterilization machines and surgeries are represented in Table 4, 5 and 6. Also, Table 7 represents the number of cases for each approach in which the approach found a better solution in comparison to others.

Table 4 is representing results when the threshold is only based on the cost of cancellation (DRSM-1). On the other hand, Table 5 represents the second approach where the threshold is a function of the number of cancellation, cost of cancellation and cost of idle time generated by the cancellation (DRSM-2). Also, Table 6 represents the KPI and improvement of our dynamic approach when surgeries assignment can be dynamically changed.

In the case of dynamic rescheduling of sterilization machines, DRSM-2 show better improvement in comparison to DRSM-1. DRSM-2's threshold is a function of cancellation cost and idle time related to each surgery cancellation and because of this

Table 4: KPI and Percentage improvement of DRSM-1

	1 OR				2 OR			
Instance	Initial KPI	Best KPI	Improvement	GAP	Initial KPI	Best KPI	Improvement	GAP
1	551.47	507.77	7.92 %	0 %	739.53	736.98	0.34 %	29.16 %
2	553.28	506.03	8.54 %	0 %	742.39	727.00	2.06 %	24.79 %
3	651.47	608.58	6.58 %	0 %	886.43	875.07	1.28 %	30.66 %
4	653.56	608.00	6.97 %	0 %	889.03	866.31	2.54 %	29.97 %
5	86.89	80.36	7.52 %	0 %	165.45	150.81	8.85 %	0 %
6	86.50	78.75	8.90 %	0 %	169.21	148.96	11.95 %	0 %
7	189.79	188.19	0.84 %	0 %	367.25	358.64	2.34 %	0 %
8	190.10	185.07	2.63 %	0 %	372.15	356.51	4.19 %	0 %
9	534.23	488.82	9.20 %	0 %	714.96	671.58	5.93 %	30.65 %
10	535.74	490.59	9.16 %	0 %	716.61	666.85	6.83 %	27.97 %
11	645.87	594.06	7.86 %	0 %	864.96	824.95	4.54 %	33.34 %
12	647.48	591.33	8.38 %	0 %	867.81	823.90	5.02 %	27.25 %
13	86.54	80.47	7.01 %	0 %	170.59	141.77	17.03 %	0 %
14	88.90	80.86	9.02 %	0 %	173.52	140.64	19.05 %	0 %
15	189.96	188.16	0.95 %	0 %	376.95	313.24	17.09 %	0 %
16	193.50	187.51	3.09 %	0 %	380.82	316.01	17.21 %	0 %
Average			6.54				7.89	

Table 5: KPI and Percentage improvement of DRSM-2

	1 OR				2 OR			
Instance	Initial KPI	Best KPI	Improvement	GAP	Initial KPI	Best KPI	Improvement	GAP
1	380.88	259.72	31.81 %	0 %	622.19	567.84	8.74 %	57.78 %
2	224.16	145.87	31.70 %	0 %	624.37	567.93	9.03 %	21.93 %
3	680.88	559.72	17.79 %	0 %	886.43	875.07	1.28 %	30.66 %
4	680.73	560.24	17.70 %	0 %	884.29	866.64	1.99 %	24.99 %
5	86.89	80.36	7.52 %	0 %	288.65	286.43	0.77 %	0 %
6	86.39	78.67	8.88 %	0 %	290.41	287.13	1.13 %	0 %
7	189.79	188.19	0.84 %	0 %	477.74	448.72	6.07 %	0 %
8	190.10	185.07	2.63 %	0 %	476.81	433.89	8.96 %	0 %
9	383.16	261.23	31.60 %	0 %	572.50	442.98	22.10 %	24.45 %
10	383.26	262.91	31.14 %	0 %	572.82	451.06	20.61 %	23.13 %
11	703.16	541.23	22.63 %	0 %	864.96	826.68	4.36 %	18.56 %
12	703.27	558.95	19.88 %	0 %	867.81	821.65	5.28 %	27.66 %
13	86.54	80.47	7.01 %	0 %	314.82	163.17	48.17 %	0 %
14	88.90	80.74	9.16 %	0 %	316.31	182.40	42.20 %	0 %
15	189.96	188.16	0.95 %	0 %	488.44	398.56	18.62 %	0 %
16	193.50	187.51	3.09 %	0 %	492.23	402.96	17.78 %	0 %
Average			15.27				13.57	

Table 6: KPI and Percentage improvement of DRR

	1 OR				2 OR			
Instance	Initial KPI	Best KPI	Improvement	GAP	Initial KPI	Best KPI	Improvement	GAP
1	490.30	453.77	7.45 %	0 %	1273.19	678.78	46.69 %	15.46 %
2	491.51	421.42	14.25 %	0 %	1263.97	650.15	48.56 %	19.96 %
3	560.30	554.79	0.98 %	0 %	1551.19	1078.68	30.46 %	6.49 %
4	562.47	537.53	4.43 %	0 %	1542.13	1045.58	32.20 %	33.44 %
5	218.97	130.64	40.34 %	0 %	532.30	390.16	26.70 %	0 %
6	218.41	120.51	44.82 %	0 %	535.82	378.17	29.41 %	0 %
7	245.57	219.03	10.81 %	0 %	1041.80	998.91	4.12 %	0 %
8	244.51	219.86	10.05 %	0 %	1044.26	975.59	6.57 %	0 %
9	501.04	416.79	16.81 %	0 %	1054.92	654.26	34.06 %	25.64 %
10	501.40	414.15	17.32 %	0 %	1051.93	661.37	33.04 %	31.54 %
11	601.78	564.96	6.20 %	0 %	1381.28	934.52	30.79 %	43.60 %
12	602.11	555.14	7.61 %	0 %	1380.94	882.49	34.68 %	45.72 %
13	227.15	127.49	43.75 %	0 %	506.63	388.49	22.87 %	0 %
14	231.14	116.07	49.58 %	0 %	513.50	379.25	25.51 %	0 %
15	257.03	219.14	14.62 %	0 %	1053.39	877.61	16.53 %	0 %
16	260.97	224.47	13.86 %	0 %	1059.96	866.54	18.07 %	0 %
Average			18.93				27.52	

function, it performs better than DRSM-1 in case of percentage improvement, where this percentage is 7.21 and 14.42 percent for DRSM-1 and DRSM-2. DRSM-2's show better improvement in cases with scarce RMD. Besides, when the cost of cancellation is high, both DRSM-1 and DRSM-2 show lower improvement. This effect is more significant in DRSM-2.

For dynamic rescheduling of surgeries approach, the pattern of results are different from DRSM. DRR works better in cases with ample initial RMD and the reason is that DRR can change the surgery's room assignment without considering the availability of RMDs. Moreover, in instances with a lower cost of cancellation, DRR's improvement is notably higher. However, this change in assignment could increase the number of cancellations.

To compare all the approaches, we compared the best KPI found in each instance for all approaches and count the number of cases in each instance when an approach founds better KPI. The results are shown in Table 7. In instances with 1 OR, DRSM-2 in comparison to other approaches found more solutions with lower KPI. DRSM-1 follows DRSM-2 with 70 good solutions, however, DRSM-1 and DRSM-2 share 61 of these solutions. When the number of ORs is increased to 2, our initial approach founds a higher number of solutions with lower KPI. When the cost of cancellation is high,

Table 7: Comparison of approaches

		1 OR				2 OR			
Instance	of instance	Main	DRSM-1	DRSM-2	DRR	Main	DRSM-1	DRSM-2	DRR
1	1	0	0	1	0	0	0	1	0
2	5	0	0	5	0	0	0	5	0
3	1	1	0	0	0	1	0	0	0
4	5	4	0	0	1	5	0	0	0
5	1	0	1	0	0	0	1	0	0
6	5	0	3	3	0	0	5	0	0
7	1	0	1	1	0	1	0	0	0
8	5	0	5	5	0	5	0	0	0
9	5	0	0	5	0	0	0	5	0
10	25	0	0	25	0	1	0	24	0
11	5	2	1	1	1	5	0	0	0
12	25	12	4	6	3	25	0	0	0
13	5	0	5	5	0	0	5	0	0
14	25	1	22	24	0	0	25	0	0
15	5	1	4	4	0	3	2	0	0
16	25	1	24	24	0	15	10	0	0
Sum		22	70	109	5	61	48	35	0

our main approaches perform better in instances with identical surgery durations SD, however in instances with heterogeneous surgery durations and low cancellation cost, DRSM approaches are work better. The reason for this behaviour is that DRSM can react to heterogeneous RMD requirement in each scenario and decide to cancel the surgery or start the sterilization machine, however, the main approach has a fix sterilization schedule and because of uncertainty in duration of surgeries, in cases when the surgury takes more than expected, we may fail to do the sterilization and it may lead to increase in number of cancellation. To avoid this problem, it schedules the machine to a period that the change in duration will not affect the sterilization.

In the case of the number of cancellations, our main approach performes better than other approaches in both single and multiple ORs. In instances with single OR DRSM-1 has a much better performance than DRSM-2, however, when the number of ORs increases, both DRSM-1 and DRSM-2 show the same performance. On the other hand, the DRR approach has the highest number of cancellations in instances with multiple ORs. The average number of cancellation for each approach is shown in Table 8.

For instances with 1 OR, as expected, instances with a higher cost of cancellation show a lower number of cancellation in the main approach and this effect is more

Table 8: Number of cancellation in approaches

	1 OR				2 OR			
Instance	Main	DRSM-1	DRSM-2	DRR	Main	DRSM-1	DRSM-2	DRR
1	0.92	1.01	3.00	1.01	1.61	1.41	3.56	4.03
2	1.05	1.02	3.00	1.13	1.68	1.45	3.84	3.85
3	0.85	1.01	3.00	0.95	0.59	1.37	1.37	4.00
4	0.91	1.01	3.00	0.99	0.50	1.33	1.33	3.69
5	0.90	1.13	1.13	1.63	0.82	2.07	0.95	6.16
6	0.90	1.09	1.09	1.41	0.97	2.08	0.95	6.41
7	0.25	1.05	1.05	0.27	0.21	2.03	0.52	5.48
8	0.28	1.05	1.05	0.28	0.08	2.05	0.61	4.78
9	1.40	1.05	2.80	1.44	1.88	1.78	3.23	3.34
10	1.33	1.07	2.96	1.35	1.87	1.79	3.19	3.47
11	0.61	1.03	2.80	0.67	0.99	1.43	1.51	2.57
12	0.82	1.15	2.96	0.79	1.04	1.46	1.45	1.93
13	0.94	1.09	1.09	1.68	1.04	1.82	1.66	5.33
14	1.04	1.08	1.08	1.57	1.25	1.81	1.72	5.52
15	0.58	1.05	1.05	0.38	0.17	1.72	0.69	4.44
16	0.68	1.05	1.05	0.38	0.13	1.72	0.70	4.33
Sum	13.42	16.94	32.12	15.94	14.83	27.32	27.25	69.34
Average	0.84	1.06	2.01	1.00	0.93	1.71	1.70	4.33

significant in instances with ample initial RMD. However, there is slight difference between this number from identical to heterogeneous surgery durations. For DRSM-1, the number of cancellation is close in all the instances, on the other hand, DRSM-2's cancellation has a direct relation with initial RMD, scarce cases show higher cancellations and vice versa. The increase in the number of ORs has no effect on the number of cancellations in the main approach. DRSM-1 reduces the number of cancellation for instances with scarce RMDs and has a higher number of cancellations for instances with ample initial RMDs. Also, we can say that the cost of cancellation's effect on DRSM-1 is too small. DRSM-2 finds better solutions in comparison to 1 OR instances. Besides the effect of initial available RMDs, with 2 ORs, DRSM-2 show a significant decrease in the number of cancellations when the cost of cancellation is high. For DRR, instances with identical surgery duration hast less cancellation than heterogeneous instances, besides, instances of ample RMDs have a higher number of cancellations in comparison to scarce RMD instances.

CHAPTER VI

CONCLUSION

In this thesis, we propose a simulation-optimization approach to reduce the effect of uncertain surgery duration on the schedule of operating rooms and sterilization machines which can be used by hospital management and service providers for decision-making purposes.

Towards this goal, we introduce 4 approaches. To analyze the approaches, 432 instances were generated and tested on each approach. The instances differ in the number of the operating room, initial available clean RMDs, RMD requirement of surgeries, cost of cancellation and standard deviation in the duration of each surgery in simulation. The quality of the solutions is measured by key performance indicator. In our approaches, KPI is the sum of cost of idle time, overtime, cancellation and sterilization. Based on KPIs found, hospital managers can select a desirable approach to increase their profit and patient satisfaction.

After analyzing the results from all approaches, our main approach in which simulates the sequence and schedule of the surgeries and schedule of sterilization machines found in the deterministic model, shows results of good quality in case of the number of cancellation for both OR1 and OR2 and KPI found in instances with 1 OR. For instances with cancellation cost lower than sterilization cost, the main approach shows an average of 20% improvement, and an average of 15% improvement in all instances.

DRSM-1 and DRSM-2 dynamically reschedule the sterilization machines and DRR dynamically reschedules the operating rooms. DRSM-2 found 75% of the best solution in instances with single OR and 25% for instances of 2 OR. Besides. it shows an average of 14.42% as a KPI improvement. DRSM-1 and DRSM-2 share 20% of best solutions for instances with single OR, however, in case of KPI improvement, an average of 7.21% is seen in DRSM-1. As a result, we can suggest DRSM-2 for the hospitals with dynamic sterilization machine schedule. DRR approach shows poor results in case of KPI in all the instances, however as an improvement approach it results in 18.93% improvement for OR1 and 27.52% for OR2, and if the service providers decide to allow reassignment of surgeries during the day DRR is a good choice.

In this thesis, we studied the scheduling of sterilization machines and surgeries with uncertainty in the duration of surgeries. As a future research direction, we can suggest working on uncertainty in the resources. RMDs availability and sterilization duration can be consider uncertain or the possibility of break down in sterilization machines can be added to the problem. In addition, the arrival of emergency patients can be added to the problem. Another avenue of research can be dynamic weights for KPIs, considering that the cost of idle time and overtime were fixed. Furthermore, we can study the effect of changing the values of alpha in the objective function of deterministic model. We can also investigate the instances that each operating room can only do certain types of surgeries.

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