Simulation Optimization of Operating Room Schedules for Elective Surgeries

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Abstract. Our specific problem is to create daily schedules of elective surgeries in a multiple operating room setting with the goals of minimizing the amount of overtime incurred and maintaining patient volumes. While surgical durations cannot always be perfectly estimated and vary by procedure and surgeon, our approach relies on leveraging the stochastic nature of surgical durations to simulate each operating day and understand the probability of incurring overtime under a certain schedule of surgeries. The heuristic optimization component of our approach investigates the probabilistic evaluation and strategically reschedules surgeries. Through experimentation with three optimization techniques, two showed promising results being able to reduce the total number of overtime surgeries by 12-15%, equivalent to approximately 1h of total monthly overtime. Compared to the literature, this approach serves solely as a tool for improving schedules and can be used for supporting decision making at the hospital. Our contribution involves introducing the simulation optimization model and describing the data-driven approach to analyzing the scheduling problem.

Keywords: simulation optimization · surgical scheduling · heuristics

1 Introduction

Operating rooms (OR) are the biggest source of costs and revenue for hospitals. On average, approximately 40% of a hospital's total expenses come from the activity of surgical staff, materials, and facilities [2]. Two-thirds of direct costs result from salaries and benefits, which include operating room staff (doctors (depending on the funding model), nurses, circulators, x-ray technicians), administrators, and managers [5]. Given the high costs of the surgical suite, efficient scheduling is paramount.

The topic of surgical scheduling has been of interest to the academic community for several decades, using multidisciplinary approaches from fields including computer science [4, 8] and operations management [23, 24]. The works

* Supported by Natural Sciences and Engineering Research Council of Canada (NSERC) through a Discovery Grant – RGPIN-2022-04524.

cover a range of approaches and techniques for finding improved ways to schedule surgeries. Exact algorithms have been used to identify optimal solutions to the scheduling problem either through programming techniques (e.g.: mixed-integer programming [18], knapsack algorithm [22], etc) or commercial tools (e.g.: CPLEX [19], XPRESS [3], GUROBI [21], etc.). Heuristic approaches have been used to find approximate solutions to large-scale scheduling problems due to their ability to provide quick, reasonably good solutions at a relatively low computational cost. Heuristic algorithm examples in surgery scheduling include genetic algorithms [15], simulated annealing [23], and local search methods [20, 25]. Simulation models have been used in surgical scheduling typically for evaluation purposes – to assess the robustness of scheduling algorithms under uncertainty. However, in recent years, a hybrid approach of simulation optimization has become a primary area of research due to its ability to handle OR scheduling complexities [10]. Discrete-event simulations (DES) and Monte Carlo simulations have been among the most popular simulation techniques [27].

Considerable interest exists in the study of surgical scheduling problems within real environments, which can enable the ultimate translation of benefits from theory to practice [10]. However, strict patient privacy policies limit the availability of open-source hospital scheduling data. Consequently, many studies rely on generated or a combination of de-identified real-world and synthetic data. One of the most recent OR scheduling benchmark sets has been proposed by Leeftink and Hans [13] to introduce a common way for solving the problems and comparing solutions. Yet comparative evaluations of performance of solutions have been rare due to differences in data.

Overall, the topic of surgical scheduling is complex due to the unique processes and structures of each individual hospital. The organizational structure, along with the set processes for coordinating and managing schedules result in distinct planing and scheduling needs. Tailoring a schedule optimization solution requires considering all of these nuances. This work aims to enhance existing scheduling solutions by recommending minimal rescheduling adjustments to reduce overtime costs and maintaining scheduling preferences.

This work is done in collaboration with the Holland Centre (part of Sunnybrook Health Sciences Centre), a stand-alone hospital in Toronto focused on elective orthopaedic surgical care, performing the highest volume of hip and knee arthroplasty in Canada. We focus on optimizing the elective surgical scheduling (primarily hip and knee and revision arthroplasty procedures) by applying heuristic optimization techniques in combination with a discrete-event simulation model. The contribution of this paper is twofold. First, we provide a methodological framework that combines simulation with optimization and effectively load balances planned surgeries, minimizing overtime. Second, we build a system that will be expanded in the future with additional scenarios, constraints, and improved techniques for surgical duration estimations.

2 Literature review

Typically, surgical planning and scheduling is divided into three levels: long-term, medium-term, and short-term. Long-term, also known as "Case Mix Problem (CMP)", focuses on allocating OR time to surgical specialities to optimize costs and profits [17, 18] or to meet long-term patient demand [6, 25]. Medium-term, also known as "Master Surgery Scheduling (MSS)", focuses on assigning surgical specialties to the specific OR time slots to optimize resource utilization [3, 4]. Short-term, also known as "Operational Level" scheduling and "Surgical Case Scheduling (SCS)", is of interest to us and focuses on assigning resources (surgeons, nurses, rooms) and patients to a specific day and time.

Díaz-López and colleagues [8] have formulated a simulation-optimization approach for daily scheduling where the goal was to maximize the utilization of ORs and to minimize delays in starting the scheduled surgeries. They modeled durations as random variables and used a greedy randomized adaptive search (GRASP) to generate an optimal schedule. The schedule performance, analyzed through a Monte Carlo simulation, provided insights into a range of solutions with some reducing wait times, and others increasing the OR utilization rate. Saadouli and colleagues [22] proposed a 3-step stochastic optimization and simulation approach where, first, a knapsack model selects operations for the day, minimizing overtime and undertime of the ORs. Next, a mixed-integer programming model assigns operations to different ORs, minimizing the room's maximum completion time and the total waiting time. Finally, a discrete-event simulation model determines the recovery bed assignment of each operated patient. Such planning showed to outperform the head surgeon's approach and suggested a gain of up to 100 additional operations annually.

To cover the range of possible simulation optimization approaches, a taxonomy was proposed by Figueira and Almada-Lobo [9] that classifies simulation optimization methods by four key dimensions, looking at the simulation purpose, structure, search method and search scheme.

Landa and colleagues [12] proposed an optimization with simulation-based iterations (OSI) to maximize the OR utilization and minimize the number of patient cancellations. The purpose of their simulation was to generate scenarios through Monte Carlo, then apply a local search and Tabu search algorithms to find the most feasible solutions in several iterations of the simulation. Liang and colleagues [14], on the other hand, employed a sequential simulation–optimization (SSO) to maximize patient throughput and minimize patient waiting time. The purpose of their simulation model was to evaluate the scheduling performance of three simple scheduling rules. The evaluation was first passed to a response surface methodology (to determine an optimal weights configuration of the simple rules) and then to a Tabu search optimizer to find an optimal combined scheduling policy. The work presented in this paper will also be in the realm of a sequential simulation-optimization in which a discrete-event simulation model is followed by a heuristic improvement technique.

In surgical scheduling, uncertainties such as patient arrivals, surgical durations, length of stay, and recovery bed availability limit the ability to create schedules that fully account for these real-world aspects. Surgical durations are particularly of interest in this paper. While some researchers focused on solving this problem deterministically, others turned to stochastic modelling. Deterministic approaches, such as machine learning techniques, have been applied to predict surgical duration based on preoperative factors [1, 26]. However, in surgical scheduling, stochastic techniques for estimating surgical durations have been more popular since they are able to incorporate uncertainty and variability of the durations. A widely adopted technique for such purposes has been drawing surgical durations from probability distribution functions (PDFs). A majority of researchers have modelled their surgical durations as one type of a PDF, such as a log-normal distribution function [24] or an exponential distribution function [16], while fewer researchers fitted surgical durations to a combination of functions depending on which function better fits the specific procedure [7, 11].

3 Problem

3.1 Description

The suboptimal scheduling of surgical procedures impacts the underutilization and overutilization of ORs. Hospital administrators face challenges in accurately estimating the duration of procedures, thereby affecting the optimality of schedules. The actual efficiency of the schedules becomes apparent only after the scheduled day ends in the real-world context.

This study aims to improve the OR load within each scheduled day by minimizing all potential overtime days within a monthly horizon. Typically, surgeries are known a month in advance, so we use that horizon to first evaluate the performance of the initial schedule, then by applying simple heuristics propose to reshuffle certain surgeries between days.

Following current clinical practice, a single surgeon is assigned to one of the 5 ORs for the full day. Each OR's end time is predefined (each room ends at either 3:30pm or 5pm), as well as the patient to surgeon assignment. In this problem we assume there are no cancellations, no emergency cases and only one surgery happens in a room at a time.

3.2 Methodology

The solution approach to the scheduling problem involves several components. First, to address the surgical duration uncertainty problem, we took all surgeries between January 2012 and May 2022, grouped all of the durations by procedure code and surgeon code, and fitted each group to several probability distribution functions to find the best function for each group. Second, we built a discrete-event simulation (DES) model to replicate the flow and processing times of surgeries (details in Section 4). For each surgery, the DES draws a stochastic duration from the distribution. Then for each day, the DES outputs the amount of overtime and undertime it incurred. Third, to optimize the way surgeries are scheduled, we applied some simple heuristic rules that rely on the schedule evaluation generated by the DES, and it reschedules surgeries from overtime days to undertime days (details in Section 5).

3.3 Analysis

Prior to formulating the solution framework, we conducted extensive data analysis using hospital Decision Support data spanning 10 years. This data included details on total hip and knee replacement surgeries, including date of surgery, surgery code, surgeon code, procedure code, estimated surgical duration and actual surgical duration. Turnover time and room features were calculated.

Initially, the problem was not clearly defined, so the data analysis efforts were aimed at investigating all factors contributing to delays between surgeries. Subsequently, we focused on OR utilization rates, including overtime and undertime incurred by existing schedules.

Analysis revealed an average turnover time of 24.89 minutes with a standard deviation of 25.08 minutes at the hospital between 2012 and 2022. The large standard deviation has been attributed to the heavily skewed distribution of turnover times. Turnover times were found to vary with each surgeon, procedure category, and anaesthetic technique used.

Long turnover times (defined as greater than the turnover mean plus one standard deviation, >50.00 minutes) occurred in 4.82% of cases, with a mean duration of 100.56 minutes and standard deviation of 61.86 minutes. Early day surgeries, between 9am and 1pm, were more likely to experience long turnover times.

Delays in turnover times were attributed in part to cases ending within 5 to 10 minutes of each other, imposing a strain on the environmental services team, who are called on to clean several rooms simultaneously. Between 2012 and 2022, 16.37% of cases ended within 5 minutes of each other in different ORs, and 30.03% ended within 10 minutes, both significantly correlating with increased turnover time (p-value <0.01). However, from 2020 to 2022, only cases ending within 5 minutes of each other were significantly correlated with longer turnover time. While statistically significant, concurrent ends of 5 minutes were found to increase turnover times by an average of only 2-3 minutes, which was determined to not be clinically significant.

In terms of overtime, in 2021, 230 cases (11.31% of total) ended in overtime, resulting in 156.33 hours of overtime for the year. On average, each month incurred 13.03 hours of overtime. As per Figure 1, most overtime occurred in rooms that were scheduled to end early (at 3:30pm). Short rooms experienced more surgeries ending in overtime, with some even ending past past 5pm (the supposed end of long rooms). Looking at undertime, it typically exceeded overtime each month, as shown in presented in Figure 2.

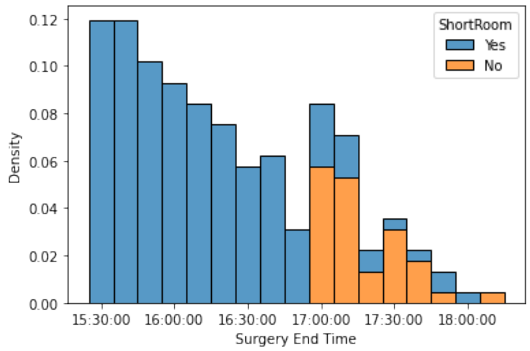

Fig. 1. Overtime incurred by Short (3:30pm) versus Long (5pm) rooms.

Finally, considering the ratio of undertime to overtime, it was determined that there is an opportunity for optimization which would involve rescheduling surgeries from overtime to undertime days to minimize both outcome parameters.

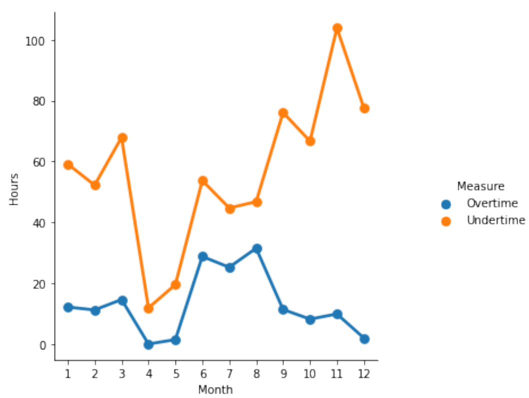

Fig. 2. Total hours of overtime compared to undertime per month.

4 Discrete-event simulation model

A discrete event simulation (DES) model was chosen for this project due its event-driven nature, allowing comprehensive modeling and evaluation of resources and events within the operating theater. Our DES evaluates original and optimized schedules, with DES outputs informing the optimization process.

In our DES model, we focus on intra-operative activities, where surgery start, surgery end, and cleaning crew activities trigger state transitions for surgeons and rooms. The model operates in simulated and actual environments. Simulated mode uses stochastic surgical durations, while actual mode employs real-world surgical durations for evaluation. The simulated environment serves as the basis for our optimization efforts, while the actual environment is used for the purpose of evaluating how well each schedule would have performed in real life.

Our solution approach begins with the simulated environment, where the DES receives the original surgery sequence as input. It simulates each day, dispatching patients to operating rooms once surgeons and rooms are available. Surgeons are randomly assigned to rooms each day, ensuring no sharing of rooms between two surgeons. The historical average of 25-minutes is allocated for turnover time between surgeries in the same room. The DES repeats each day's simulation 1,000 times, providing probabilistic evaluations of daily overtime and undertime minutes. The output of the DES includes average overtime and undertime minutes in each individual room, as well as the total for the day.

5 Optimization techniques

Several heuristic optimization techniques were considered in the pursuit of optimizing the surgical schedule. Three techniques were ideated, two of which involved allocation scheduling (determine the specific time of each surgery), where the third one involved advance scheduling (determine only the day of each surgery). While allocation scheduling techniques are useful for managing the day to day schedule, they do not address the issue of underutilized or overutilized rooms. Thus, an advance scheduling technique was chosen to address the issue by switching the surgeries between overtime and undertime rooms within a monthly horizon.

The goal of the technique was to not only address the evident issue of overtime, but also to maintain as much of the original sequence of surgeries as possible. Many of the scheduling works in the literature focus on optimization techniques that construct a schedule based on certain assumptions or constraints, whereas our work focuses on improving the existing schedule that was devised by the surgeons. This approach aims to empower surgeons by evaluating the proposed schedules and suggesting certain re-schedules that would improve the overall utilization of the rooms, leading to less financial losses due to over or under used staff hours.

The reshuffling heuristic technique takes the original sequence of surgeries for the month and switches certain surgeries between days in order to minimize the probability of cases ending in overtime. Since a considerable amount of surgical days end in overtime, mainly due to imperfect estimations of the surgical durations, the first step of the technique is to simulate each day in the monthly schedule 1,000 times using stochastic durations to pick out the days that were most likely to end in overtime.

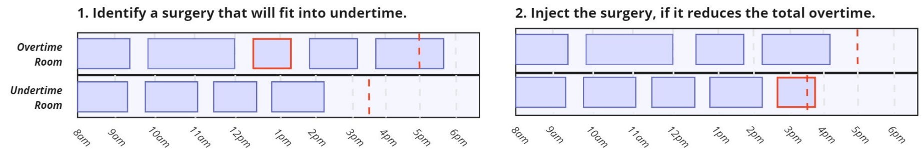

Fig. 3. Injection model

After the probabilistic estimate of overtime is created for each scheduled day, the days with the highest probability of surgeries going into overtime are taken to identify the surgeries with the largest mean and standard deviation. These are the surgeries that are most likely to cause unforeseen problems with the schedule. By identifying the days with the lowest probability of surgeries going into overtime, we are able to swap in the long-duration surgeries into those days and swap out the shorter-duration surgeries. The constraints include making sure that surgeries are swapped between the same surgeon and that the length of the day does not change.

6 Computational experiments

6.1 Experimental framework

We analyzed surgical operations data from the last 7 months of 2021, consisting of 1,415 surgeries, aiming to minimize overtime. We excluded the initial 5 months due to COVID-19 restrictions. Three reshuffling models were experimented with: "injection", "swapping", and "combined".

The injection model reduces overtime by moving the longest and most variable surgeries from overtime rooms to undertime rooms. The algorithm iterates through each overtime day and room, attempting to remove a surgery from the overtime day and room, and inject it into an undertime day and room of the same surgeon.

The swapping model reduces overtime by swapping long, highly variable surgeries from overtime days with short, less variable surgeries from undertime days. The feasibility of swaps is determined by analyzing the impact on overtime and undertime in both rooms.

The combined model merges the injection and swapping techniques, choosing the most effective model based on their impact on overtime and undertime in both rooms. The algorithm iterates through each overtime day and room, checking the feasibility of each technique, and accepting or rejecting them.

We illustrate the combined model's process through two illustrations. Figure 3 showcases the injection model in action, whereas Figure 4 showcases the swapping model. Under a close quantitative evaluation, the swapping technique is able to achieve less total overtime in both rooms, leading the combined model to chose this technique.

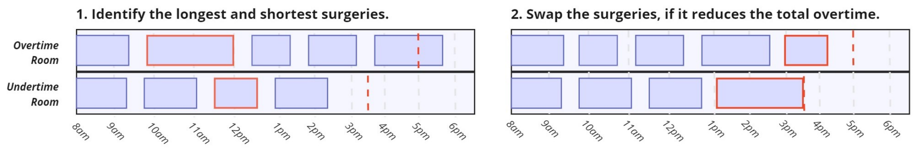

Fig. 4. Swapping model

6.2 Results

The estimated schedule prepared by the hospital initially includes overtime and undertime. However, the actual schedule encountered an average of 37 minutes more overtime and 105 minutes (1 hour and 45 minutes) more undertime per month than estimated.

Optimized schedules from various models were evaluated using a discrete event simulation (DES) in both simulated and actual environments. Compared to the original schedule, the injection and combined models showed the most significant reductions in total overtime minutes, achieving approximately 43.95% and 42.26% reductions under the simulated environment. In the actual environment, these models achieved around 10-11% reductions, equivalent to 6 hours of total overtime reduction, with an average of 1 hour reduction of overtime in each month if the schedule was implemented in real life. In terms of undertime, the injection model would have incurred 1 hour less total undertime and the combined model 6 hours less total undertime compared to the original schedule.

In contrast, the swapping model only achieved a 14.17% reduction under the simulated environment and performed unfavorably in the actual environment, resulting in more overtime than the original schedule. This is largely due to estimation errors in stochastic durations and the prevalence of undertime issues, better addressed by the injection technique. Results of total overtime and undertime hour reductions are presented in Table 1.

Table 1. Total improvement of schedules under simulated and actual environments.

Comparison	**Schedule**	**Total Overtime**	**Improvement**	**Total Undertime**	**Improvement**
Simulated durations	Original	71:52	-	278:37	-
	Injection	40:17	43.95%	270:08	3.04%
	Swapping	61:41	14.17%	274:54	1.33%
	Combined	41:30	42.26%	266:08	4.48%
Actual durations	Original	57:46	-	240:16	-
	Injection	51:28	10.93%	239:13	0.44%
	Swapping	60:00	-3.84%	237:20	1.22%
	Combined	51:46	10.40%	234:15	2.50%

In terms of the number of surgeries ending in overtime, the injection and combined models reduced this number by 26.48% and 25.52% under the simulated environment, and by 15.28% and 12.16% under the actual environment.

Certain months, like July, August, and September, experienced larger reductions, highlighting the impact of original overtime and undertime distributions on outcomes. Table 2 shows the ability of each model to reduce the number of surgeries ending in overtime.

Table 2. Total reduction of number of overtime surgeries compared to the original schedule. Positive values indicate a reduction in overtime; negative values indicate an increase in overtime.

	Injection		**Swapping**		**Combined**	
	Simulated	Actual	Simulated	Actual	Simulated	Actual
Jun	10.66%	1.19%	2.99%	-3.56%	14.59%	5.46%
Jul	45.00%	35.42%	9.74%	-3.47%	47.39%	24.77%
Aug	27.21%	20.81%	-6.77%	2.64%	26.87%	19.40%
Sep	28.02%	9.66%	1.24%	-16.91%	29.24%	16.91%
Oct	10.10%	8.76%	14.59%	17.52%	9.23%	0.00%
Nov	-4.15%	-15.63%	-4.07%	0.00%	-43.52%	-28.13%
Dec	51.01%	0.00%	-4.52%	26.32%	1.27%	-26.32%
Grand Total	**26.48%**	**15.28%**	**2.57%**	**-0.57%**	**25.52%**	**12.16%**

7 Discussion and Conclusions

We developed a simulation optimization model to improve monthly surgery schedules, aiming to reduce overtime and undertime. Two prominent reshuffling models achieved a 12.16% and 15.28% reduction in the number of overtime surgery ends, resulting in a 10-11% actual reduction in overtime compared to the original schedule, equivalent to saving an hour of overtime every month.

Our approach has limitations. Firstly, it focuses on optimizing existing schedules rather than building them from scratch. However, this also serves as one of the advantages of the approach since it aims to preserve the schedule of surgeries that has been prepared by surgeons (considering staff availability, surgery urgency, and other factors) and only makes suggestions in terms of surgeries that should be rescheduled for a more optimal schedule. Secondly, our stochastic duration approximation isn't highly accurate, which hinders our evaluation efforts, necessitating real-world testing. However, prediction of surgical durations is an open research topic. Future work includes additional testing of our proposed technique using hospital data.

While this paper presents findings that led to viable solutions, others approaches were considered For instance, we initially discussed with hospital stakeholders the possibility of reshuffling the daily sequence of surgeries in each room. The objective was to reduce the number of cases that end concurrently, to relieve the strain on the environmental services team contributing to delays and overtime. However, after a thorough data analysis, we concluded that even though concurrently ending cases are a statistically significant issue, in the context of our hospital settings, a 2-3 minute addition was not considered to be clinically significant at our institution. Nonetheless, re-sequencing of daily surgeries might be something interesting to consider at other hospitals.

There are several contributions of this paper. Firstly, this work offers a methodological and data-driven framework that can be employed by other researchers and hospitals aiming to enhance their operating room (OR) scheduling. Secondly, and most important, the proposed system establishes a foundation for future theoretical research, advancing the area of surgery scheduling.

In the future, other scenarios may wish to consider the impact of emergency cases, along with evaluating upstream and downstream facilities and resources. Further stochastic surgical duration estimation experimentation would be necessary to incorporate additional features with the aim of better representing complex relationships between factors that influence surgical durations. Lastly, the proposed solutions require testing within hospital settings which requires the development of a user-friendly interface to allow access to the schedules and the ability to present alternate plans to hospital staff.

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