Journal of Scheduling (2025) 28:545–562
https://doi.org/10.1007/s10951-025-00851-2

Designing a long-term master surgical timetable: a case study in balancing post-operative ward bed demand and minimizing changes in surgical schedules

Rafael Calegari[1] · Flavio S. Fogliatto[1] · Filipe R. Lucini[2] · João B. G. Brito[1] · Gabrielli H. Yamashita[3] · Michel J. Anzanello[1] · Guilherme L. Tortorella[4,5] · Beatriz D. Schaan[6,7]

Accepted: 1 July 2025 / Published online: 4 August 2025

Abstract

Peaks in patients' demand for inward hospitalization usually lead to disruptions in the provision of healthcare, negatively affecting patient and staff satisfaction. The two main sources of ward bed demand are the emergency department and the surgical center; while the former is random by nature, the latter can be managed through proper allocation of surgical specialties to time slots (or blocks) in the center's timetable (Master Surgical Schedule—MSS) and efficient scheduling of surgical procedures within time slots across specialties. This case study explores the proposition and application of a three-step method to design a long-term MSS timetable at a tertiary public teaching hospital. In step 1, historical data are mined to determine the average duration of surgical procedures and the average length of stay in wards for each surgical specialty. Step 2 applies a genetic algorithm to generate a timetable that balances the overall ward bed demand across the planning horizon. In step 3, an alignment heuristic is employed to adjust the new timetable to resemble the hospital's current MSS, minimizing disruptions to existing operations. The method was tested using data from the hospital, resulting in a significant reduction in post-operative ward bed demand variability by 99.9%, while retaining 97% of surgical specialties in their original slots. This case study presents the first approach for long-term MSS design that balances post-operative ward bed demand while minimizing changes to the current surgical teams' schedules, emphasizing solutions that promote minimal disruption to hospital operations. Furthermore, the proposed method is adaptable for use in other hospitals with similar characteristics, offering a flexible solution to managing changes in surgical and ward bed demand.

Keywords OR in health services · Master surgical schedule · Operating room timetable · Ward bed demand variability · Case study

1 Introduction

The operating room scheduling problem (ORSP) is a combinatorial optimization problem that involves allocating patients to operating rooms (ORs), considering constraints on time and available resources (Hamid et al., 2019). Various objective functions guide ORSP solutions, such as maximizing resource utilization or minimizing operational costs. ORSP's significance lies in its potential to generate substantial financial resources while incurring high operational costs.

The ORSP can be decomposed into three decision levels: strategic, tactical, and operational (Guerriero & Guido, 2011). At the strategic level, decisions involve long-term alignment of surgical center operations with organizational goals. This includes solving three subproblems: capacity Planning (determining necessary resources, such as ORs, based on forecasted demand), Case-Mix (deciding surgery types and patient volume per specialty), and Capacity Allocation (assigning OR times to specialties to meet anticipated patient demand). At the tactical level, the ORSP is termed master surgery scheduling (MSS). Its aim is to establish a master plan, typically monthly or quarterly, detailing resource utilization such as available ORs, opening and closing times, and priority specialties/surgeons for using time blocks. This involves allocating surgical groups to predict total surgeries based on recurring specialty profiles. This study focuses specifically on this tactical level, analyzing the case of a hospital with a block scheduling policy, where allocation of specialties to OR time slots remains static over the long term. At the operational level, the ORSP becomes

Extended author information available on the last page of the article the surgery scheduling problem (SSP), which is further subdivided into Advanced Scheduling (surgical case allocation with a defined date for each operation) and Allocation Scheduling (surgical case scheduling with exact start times and allocation of surgical center resources). Recent literature reviews on the ORSP (Abdalkareem et al., 2021; Harris & Claudio, 2022; Melo & Fogliatto, 2025) indicate that most publications concentrate on the operational level. In some healthcare settings, such as clinics and private hospitals, MSS and SSP are often addressed jointly (Melo & Fogliatto, 2025; Testi & Tanfani, 2009).

In systems with high surgical demand and limited ward beds, post-operative bed availability is a critical concern. Elective surgeries may be canceled when no ward beds are available, and the timing of surgical procedures directly influences post-operative bed demand. Each surgery has an associated length of stay (LOS), contributing to variations in patient throughput and potentially disrupting the service flow in critical areas such as surgical wards and recovery rooms (Fügener et al., 2016). While the occurrence of illness and injury naturally fluctuates, the demand for inpatient care is also heavily influenced by surgical scheduling. Artificial peaks in demand, resulting from the concentration of elective surgeries on particular days, often lead to unforeseen events such as overcrowding in post-operative recovery areas or insufficient ward bed capacity. Previous research has shown that artificial peaks and valleys in patient flow can be analyzed and smoothed using scheduling models, leading to improvements in resource use and reducing waste (Harrison et al., 2005; Ryckman et al., 2009).

This case study investigates a method for designing a long-term MSS that aims to balance post-operative ward bed demand while minimizing disruptions to existing surgical schedules. Our method addresses the specific challenges of a large public university hospital in southern Brazil, where the goal is to reallocate surgical specialties to time slots in a way that stabilizes bed demand and reduces cancelations or modifications to surgical procedures. We present a three-step approach to MSS design tailored to the characteristics of this hospital's surgical center. The first step involves analyzing historical data to estimate the typical duration of surgical procedures and post-operative LOS for each specialty. The second step applies a genetic algorithm to generate a timetable that optimizes the overall ward bed demand throughout the planning horizon. Finally, the third step aligns this timetable to the hospital's existing surgical schedule in order to minimize changes.

The case study illustrates how to improve the surgical center's operational efficiency by balancing bed demand while maintaining a stable surgical timetable. The hospital's current MSS, which has been in use for several years with minimal changes, provides a baseline for comparison. The objective is to create a new timetable that retains the existing allocation of surgical specialties to time slots as much as possible, with minimal disruption to ongoing hospital operations. This approach offers a practical solution to a common challenge in teaching hospitals, where surgeons have teaching and supervision duties that must be reconciled with their role in the surgical center and their private practice. Long-term, static MSSs are particularly common in these cases; the strategic and tactical decision levels communicate when designing the MSS, while decisions at the operational level belong exclusively to that level, i.e., the MSS is planned to remain static in the long run (12–60 months), while the SSP is revisited weekly or daily. The method proposed here may be adapted for use in other institutions with similar characteristics.

2 Background

Variability in demand for any service is a significant barrier to the efficient distribution of limited resources (McManus et al., 2003). When peaks of demand cannot be accommodated, it may cause restrictions on access to care. Patient safety is also affected, as treatment delays and patients being placed in the wrong care unit may lead to adverse events and poorer outcomes (Ryckman et al., 2009). Hospitals traditionally answer to increased demand by adding resources—more staff and beds. However, research has demonstrated that efficiency can be improved through streamlining of patient flow and redesigning of care processes (Litvak & Bisognano, 2011).

The operating room scheduling problem (ORSP) has been widely reported in the literature, being the subject of several literature reviews, each organizing the problem under different lenses. Cardoen et al. (2010a) analyze the literature under six perspectives: patient characteristics, performance measures, decision delineation, research methodology, uncertainty, and research applicability. More recently, Zhu et al. (2019) reorganized Cardoen et al. (2010a)'s perspectives and updated the literature. May et al. (2011) organized the literature into six categories: capacity planning, process redesign, surgical services portfolio, estimation, procedure duration estimation, monitoring, schedule construction, and control. Finally, Kim et al. (2014) proposed a research framework to analyze the literature on the case-mix, master surgery scheduling, and surgery scheduling problems.

Hans et al. (2012) propose a framework for healthcare planning and control deploying the problem according to the managerial area (medical planning, resource capacity planning, materials planning, and financial planning) and hierarchical decomposition (strategic, tactical, offline operational, and online operational). The block planning problem, which we generally denote here by MSS, is positioned at the intersection of the resource capacity planning area and the tactical hierarchical level. Such planning is typically conceived for long to medium-term horizons; in short-term plans, the MSS and SSP are usually treated jointly, e.g., Agnetis et al. (2014), Spratt and Kozan (2016), Assad and Spiegel (2019).

As reported by Zhu et al. (2019), approaches to MSS are typically limited to elective patients, analyzing surgical centers with dedicated ORs for emergency cases. Recent studies that combine elective and emergency patients in MSS are due to Bovim et al. (2020) and Ghasemkhani et al. (2020). They essentially combine stochastic optimization to account for the uncertainty in arrivals of emergency patients and simulation to check the operational impacts of the proposed MSSs in the SSP.

Several authors (e.g., Li et al., 2017; Testi et al., 2007) plan MSSs disregarding the impacts of block planning on the wards, arguing that in the long run, bed availability does not constrain the efficient flow of patients. However, some works consider the effect of MSS on the wards or the intensive care unit (ICU), resembling the situation addressed in our work.

van Oostrum et al. (2008) propose a mathematical program containing probabilistic constraints associated with procedure duration within specialties to model the MSS problem. Average patient LOS associated with specialties are used in their formulation. A two-phase column generation approach is used to handle the problem's computational complexity; it first maximizes the OR utilization and then levels the demand for downstream resources, such as wards and intensive care units. The approach was tested using data from a large Dutch university hospital. Results are discussed with respect to OR utilization and hospital bed leveling. However, no observations are made on the differences between current and proposed timetables and difficulties associated with their practical implementation.

The proposition in Beliën et al. (2009) most resembles the one presented in our paper. They propose a quadratic MIP model in which the objective function is a weighted sum of the mean and variance of bed occupancy in the hospital wards, calculated over all days in the timetable. The time slots allocated to specialties vary in duration, being constrained by the total daily time available in the OR. The model is solved using a simulated annealing heuristic. They analyze the case of a Dutch hospital with 9 ORs and 14 surgical specialties and measure the improvement from using the proposed timetable compared to the current one in terms of reduction in bed shortages. The impacts of adopting the new timetable that differs greatly from the current one are not discussed.

Adan et al. (2011) analyze a timetable that changes to respond to events in the SSP, such as short-term resource unavailability and rise in patient waiting times and competing demands of emergency patients. They propose an optimization to establish the MSS with reserved capacity for emergency patients, followed by a simulation to devise SSPs for different arrival scenarios of elective and emergency patients on a weekly and daily basis. Patients are stratified into homogeneous groups according to their demand profile on resources, capturing variations in ICU and ward bed LOS. The two-step planning strategy is tested using data related to thoracic surgery obtained from a Dutch Thorax Center.

Ma and Demeulemeester (2013) propose a framework to the ORSP in which decisions are deployed top-down, from long-term MSS to cyclic MSS and SSP. The MSS is first modeled as a deterministic integer linear programming problem aimed at maximizing resource efficiency (case-mix planning phase). The MSS is then refined by incorporating the information on ward patients' LOS variance into a mixed integer programming with the objective of improving resource utilization (master surgery scheduling phase), which is then iteratively evaluated through simulation to obtain an SSP plan. The proposition is not applied in a real-case scenario but illustrated using simulated data. Similar to our proposition, the long-term MSS is set as a deterministic problem.

As discussed above, the problem of allocating OR time slots to different surgical specialties has been mostly formulated as a MIP (Mixed Integer Programming) or BIP (Binary Integer Programming), with solutions obtained through heuristics. The problem quickly becomes strongly NP-hard as the number of ORs and specialties increases (van Essen et al., 2012). Although optimal solutions cannot be determined at reasonable computational times, good-quality solutions may be obtained using heuristics. A number of them have been proposed in the literature (Zhu et al., 2019). In general, approaches may be divided into those that use refining (Fügener et al., 2014) or constructive (Hans et al., 2008) heuristics. Refining heuristics improve on an existing solution, as observed in Roshanaei et al. (2020) and Heider et al. (2020), while in constructive heuristics, an initial solution is constructed and refined iteratively toward an objective (e.g., Akbarzadeh et al., 2020; Bovim et al., 2020; Marques et al., 2019). We combine both approaches by using a constructive heuristic to find the best MSS solution and then a refinement heuristic to improve that solution such that it resembles the timetable currently at use in the surgical center. The refinement step is an original contribution of this paper.

Meta-heuristics may be used in MSS planning; they usually provide good solutions in a shorter computational time when compared to optimization algorithms, iterative methods, or simple heuristics (Zhu et al., 2019). Genetic algorithms (GAs) are a popular meta-heuristic used in MSS planning, as reviewed by Zhu et al. (2019) and Cardoen et al. (2010a). Marchesi and Pacheco (2016), for example, assessed GA performance in the development of timetables for four different demand scenarios. Their goal was to minimize unmet demand. They were able to verify the performance of fourteen configurations of GAs with respect to the optimal solution, given the small dimension of the surgical center under analysis (5 ORs and six surgical specialties). The best GA configuration led to the optimal solution being recommended for larger-scale problems. A similar recommendation was made by Guido and Conforti (2017) and Roland et al. (2010). In Guido and Conforti (2017), a formulation for the MSS problem was proposed in which preferences of surgical teams were also considered.

Planning and scheduling of surgical procedures (i.e., decisions at tactical and operational levels of the ORSP) affect not only the performance of ORs but also of related facilities such as the post-anesthesia care unit, the intensive care unit, and hospital wards (Cardoen et al., 2010b; Heider et al., 2020). When planning the operation of surgical centers, it is key to look for plans that level the flow of patients from surgery to those units. The method proposed in this paper deals with the scheduling problem in surgical centers at an aggregate level, handling the allocation of specialties to time slots in the ORs over a given horizon and using a deterministic approach. Such allocation is expected to remain static in the long run; in opposition, the scheduling of surgical procedures within time slots is dynamic and revised on a daily or weekly basis, relying on simulation or integer programming heuristics and taking into consideration the uncertainty of events derived from the OR operation, e.g., Testi et al. (2007). Dealing with the optimization of surgical centers at an aggregate level to create a long-term MSS is the focus of our case study. We innovate by proposing a method that not only balances demand for OR downstream resources but also searches for allocations that minimize changes in the current timetable, being suitable for surgical centers already in operation.

3 Problem description

This is a case study conducted in an 842-bed tertiary care teaching public hospital located in southern Brazil. Fifteen surgical specialties operate in the hospital's surgical center. They are listed in Table 1, which also shows data for the last five years of performed surgeries by each specialty (n_i).

An *operating room* (operating theater or operation suite) is a specific room in which surgeries can be performed. The *operating center* of the hospital has 11 operating rooms (ORs) available for elective surgeries. A *time slot* is a six-hour period in an OR, either in the morning, afternoon, or evening, which can be allocated to a surgical specialty (or may also remain unoccupied). Hence, there are 33 time slots available each day. Most specialties operate every week, but some operate every other week. Therefore, the allocation of time slots to surgical specialties must consider a two-week horizon (10 working days) to account for the current workload of each specialty—that translates to 330 time slots that can be either allocated to a surgical specialty or remain empty if there is no demand (or budget, considering that it is a government-funded hospital) for procedures.

The *surgical center elective timetable* (referred hereafter as *timetable*) is defined as the matrix of ORs and time slots allocated to each specialty on each day of the planning horizon. The current timetable has been used for several years, with few changes in the allocation of specialties to timeslots. The timetable's static nature is typical of large teaching hospitals in Brazil since surgical team members must accommodate several other activities (e.g., teaching, supervising, and private practice) in their rather inflexible weekly schedules. A new surgical center with 40 ORs is due to start operating in 2023 at the hospital. The analysis reported here is a pilot study that will be upscaled to produce the new surgical center timetable.

The current timetable configuration in the surgical center of our case study is presented in Table 2. ORs #9 and #12 are exclusively dedicated to urgent and cardiac surgeries and are managed separately, not being considered in our analysis. OR #2 is equipped for robotics surgery, serving demands from five specialties (Digestive System, Urology, Private, General, and Gynecology and Obstetrics).

The current timetable was not specifically designed but rather resulted from the natural workflow of specialties and years of negotiations and adjustments. This arrangement, common in many surgical centers, may produce unforeseen and unwanted results. For example, there may be a concentration of specialties with complex procedures using ORs on the same day; this means that several patients admitted on that particular day will have longer LOS, leading to a lack of beds and possibly canceling other procedures scheduled for the next days. On the other side, a concentration of specialties with low complexity procedures on the same day will determine that several patients are admitted on that particular day at the same time in the post-operative recovery room, leading to overcrowding and a higher chance of adverse events.

Our goal was to redesign the timetable (i.e., reallocate surgical specialties to time slots), observing the following constraints: (a) maintain the current total time allotted to each specialty; and (b) do not alter specialties allocated to OR #2. The new timetable should (1) balance the expected number of post-operative hours of hospital stay along the planning horizon so that that ward bed demand will be more stable and (2) promote the smallest possible number of changes with respect to the current timetable.

This research was approved by the Hospital de Clinicas de Porto Alegre (HCPA) Ethics Committee under project number CAAE 33705014.8.0000.5327, and the authors have complied with the recommendations of the Declaration of Helsinki. Data used in the method were extracted from the hospital's management system; patients' personal data were preserved.

Table 1 List of surgical specialties and associated relevant information

Specialty, i		n_i	t_i	sd_i	s_i	d_i	h_i
1. Pediatrics	PED	2963	1403.36	361.1	12	1.65	386.01
2. Colorectal	CRT	2516	651.46	178.6	8	3.52	382.48
3. Neurosurgery	NEU	2392	637.57	137.3	10	4.05	430.79
4. Digestive System	DIG	9930	528.73	141.8	23	3.4	299.73
5. Urology	URO	11,136	526.64	136.4	25	2.63	231.17
6. Vascular	VAS	3435	525.74	130.1	12	3.03	265.32
7. Plastic	PLA	1663	493.35	161.7	8	3.63	298.23
8. Thoracic	THO	3213	458.63	88.0	10	3.48	266.07
9. Private	PRI	14,949	419.84	98.7	48	3.22	225.76
10. General	GEN	9294	377.37	101.2	22	3.03	190.38
11. Orthopedics and Traumatology	ORT	6468	312.08	71.1	22	3.18	165.37
12. Gynecology and Obstetrics	OBG	5398	210.51	85.6	18	2.61	91.4
13. Otorhino	OTR	5652	204.33	43.6	18	2.96	100.82
14. Oral and Maxillofacial	OMF	278	178.84	23.7	2	3.9	116.36
15. Mastology	MAS	2034	72.57	18.4	6	2.93	35.48
16. Undefined	Und	0	0	0	86	0	0

4 Method

In this section, we present the method designed to improve the hospital's MSS timetable, aiming to balance the number of post-operative hours of hospital stay required by the surgical center each day on a 10-day horizon. The method was carried out in three steps: 1. Determine the average duration of surgical procedures and the average number of hours of hospital stay in wards required by each surgical specialty; 2. Determine a good quality timetable that balances post-operative bed demand in wards over the planning horizon using a genetic algorithm; and 3. Approximate the new timetable to the current timetable through an alignment heuristic.

a. Step 1

Allocating a surgical specialty i to a time slot in the surgical center's timetable will enable the performing of a number of procedures, which is dependent on the average duration of procedures in that specialty (denoted by d_i). In this step, we mined a database of surgeries performed by each specialty in the past five years. The number of records n_i used to estimate d_i for each specialty i ($i = 1, \ldots, 16$) is given in Table 1.

From the same database, we calculated the average number of post-operative hours of hospital stay (denoted by h_i) demanded by each specialty. Statistic h_i is a weighted average, which considered the average number of post-operative hours of hospital stay demanded by each type of procedure within specialty i and their frequency of occurrence in the database.

Combining the information above, we determined the statistic t_i, which gives the average number of post-operative hours of hospital stay resulting from allocating specialty i to any 6-h time slot. Note that t_i is obtained by multiplying the average number of procedures that could be performed by specialty i in a time slot (which is a function of d_i) by the average number of post-operative hours of hospital stay resulting from that (which is given by h_i). Values of t_i (in hours) are given in Table 1. Two remarks must be made regarding the information on that table. First, 86 time slots in the timetable are empty, mostly from the night shift. They correspond to the *Undefined* specialty in Table 1 and were given a value of $t_i = 0$; apart from *Undefined*, 15 surgical specialties operate in the surgical center, as stated in the problem description. Second, although being a public hospital, HCPA is allowed to rent 48 of its surgical time slots to private practice from any specialty. They correspond to the *Private* specialty in Table 1, with corresponding t_i value calculated determining the percentage historical demand for rooms from each specialty. The *Private* specialty is the only one occupying some timeslots in the night shift.

b. Step 2

This is the step in which the optimal assignment of specialties to time slots is determined. The timetable of the case study's surgical center may be represented as a matrix with 33 rows (representing 11 ORs that operate three shifts a day) and 10 columns (representing the ten working days required for each specialty to be allocated at least once in the timetable). Each matrix cell represents a 6-h time slot, and there are 330 available slots. Once specialties fill out a given matrix column, it is possible to calculate the sum of their corresponding t_i values, which will inform the total number of

Table 2 Current surgical center's timetable

Room	Shift	Week 1					Week 2				
		Mon	Tue	Wed	Thu	Fri	Mon	Tue	Wed	Thu	Fri
1	*M*	PRI	PLA	THO	OMF	PLA	PRI	PLA	THO	GEN	PLA
	A	PRI	PLA	THO	OMF	PLA	PRI	PLA	THO	GEN	PLA
	E	PRI					PRI				
2	*M*	GEN	DIG		OBG	URO	GEN	DIG		OBG	URO
	A	PRI	PRI				PRI	PRI			
	E										
3	*M*	OBG	OBG	MAS	OBG	OBG	OBG	OBG	MAS	OBG	OBG
	A	OBG	OBG	MAS	OBG	OBG	OBG	OBG	MAS	OBG	OBG
	E										
4	*M*	VAS	ORT	ORT	ORT	NEU	VAS	ORT	ORT	ORT	NEU
	A	ORT	ORT	ORT	ORT	NEU	ORT	ORT	ORT	ORT	NEU
	E	PRI	ORT				PRI	ORT			
5	*M*	DIG	DIG	DIG	GEN	PRI	DIG	DIG	DIG	GEN	PRI
	A	DIG	DIG	GEN	GEN	PRI	DIG	DIG	GEN	GEN	PRI
	E					PRI					PRI
6	*M*	PED	PRI	PED	VAS	PED	PED	PRI	URO	VAS	PED
	A	PED	PRI	PED	DIG	PRI	PED	PRI	PED	PED	PRI
	E		PRI	PED				PRI	PED		
7	*M*	OTR	GEN	OTR	OTR	OTR	OTR	GEN	OTR	OTR	OTR
	A	OTR	OTR	OTR	OTR	OTR	OTR	OTR	OTR	OTR	OTR
	E										
8	*M*	URO	URO	PRI	URO	URO	URO	URO	PRI	URO	URO
	A	URO	URO	PRI	PRI	URO	URO	URO	PRI	PRI	URO
	E	URO		PRI	PRI		URO		PRI	PRI	
10	*M*	ORT	VAS	DIG	GEN	URO	ORT	VAS	DIG	GEN	URO
	A	VAS	ORT	DIG	GEN	URO	VAS	ORT	DIG	GEN	URO
	E	URO	PRI		DIG		URO	PRI		DIG	
11	*M*	CRT	DIG	CRT	CRT	THO	CRT	DIG	CRT	CRT	THO
	A	MAS	DIG	THO	CRT	THO	MAS	DIG	THO	CRT	THO
	E										
13	*M*	GEN	GEN	NEU	ORT	VAS	GEN	GEN	NEU	ORT	VAS
	A	GEN	NEU	PRI	PRI	VAS	GEN	NEU	PRI	PRI	VAS
	E		NEU	PRI	PRI	PRI		NEU	PRI	PRI	PRI

post-operative hours of hospital stay required for that day. The optimal allocation of specialties to slots in the timetable is the one that minimizes the variance of the sums of t_i values calculated for each weekday, overall weekdays in the timetable. Any timetable resulting from applying our method must respect the current demand for time slots presented by each specialty.

Let matrix $T_{m \times n}$ represent the timetable, with m $(= 33)$ rows and n $(= 10)$ columns. Each matrix cell corresponds to a binary decision variable defined as a_{jki}, such that $a_{jki} = 1$ indicates that surgical specialty $i (= 1, \ldots, 16)$ is allocated to room/shift $j (= 1, \ldots, 33)$ on day $k (= 1, \ldots, 10)$, and $a_{jki} = 0$ indicates otherwise. The problem to be optimized has the objective function in Eq. (1), that seeks the minimum variance of column sums overall days in the timetable, which are calculated using eqns. (2) and (3), a set of restrictions in Eq. (4) that assures that demand for time slots by each surgical specialty (informed in Table 1) is satisfied, Eqs. (5) to (9), associated with OR #2, in which a restricted number of specialties operate (see Table 2), and a set of restrictions in Eq. (10) that assures that no specialties other than those listed in Eqs. (5) to (9) operate in OR #2.

$$\text{Min } z = \frac{\sum_{k=1}^{10}[x_k - \overline{x}]^2}{n-1} \tag{1}$$

s.t.

$$x_k = \sum_{j=1}^{33}\sum_{i=1}^{16} t_i a_{jki}, \quad k = 1, \ldots, 10 \tag{2}$$

$$\overline{x} = \left(\sum_{k=1}^{10} x_k\right)/10 \tag{3}$$

$$\sum_{j=1}^{33}\sum_{k=1}^{10} a_{jki} = s_i, \quad i = 1, \ldots, 16 \tag{4}$$

$$\sum_{i=1}^{16} a_{jki} \leq 1, \quad j = 1, \ldots, 33; \quad k = 1, \ldots, 10 \tag{5}$$

$$\sum_{j=4}^{6}\sum_{k=1}^{10} a_{jk4} = 2 \tag{6}$$

$$\sum_{j=4}^{6}\sum_{k=1}^{10} a_{jk5} = 2 \tag{7}$$

$$\sum_{j=4}^{6}\sum_{k=1}^{10} a_{jk9} = 4 \tag{8}$$

$$\sum_{j=4}^{6}\sum_{k=1}^{10} a_{jk10} = 2 \tag{9}$$

$$\sum_{j=4}^{6}\sum_{k=1}^{10} a_{jk12} = 2 \tag{10}$$

$$\sum_{j=4}^{6}\sum_{k=1}^{10} a_{jk12} = 0, \quad i = 1, 2, 3, 6, 7, 8, 11, 13, 14, 15, 16 \tag{11}$$

Equations (1) to (5) can be generalized by adjusting the summation limits, which correspond to the number of surgical specialties operating in the surgical center and the duration of the MSS planning horizon. Equations (6) to (11) delineate constraints specific to the case study and may not be applicable in other scenarios.

To overcome the computational intractability and find a good quality solution to the timetable problem, we apply a Genetic Algorithm (GA), a metaheuristic inspired by the process of natural selection and evolution (Martin & Spears, 2001), often used in MSS problems (Zhu et al., 2019). An initial population is generated with a set of chromosomes that represent possible solutions to the optimization problem. At each step of the evolutionary process, the population is evaluated regarding a fitness function, and each chromosome is given a fitness value that reflects the performance of the solution if that chromosome is chosen. Those with the best fit are selected and may be further modified in their fundamental characteristics through genetic operators (e.g., crossover and mutation) to produce a second-generation population of solutions. The process is repeated until a termination condition is reached. The four main elements of GA are chromosome encoding, initial population generation, fitness evaluation, and genetic operators.

Chromosome encoding varies according to the type of problem and data and how they are structured. Encodings may be binary, octal, hexadecimal, permutation, value, and tree (Kumar, 2013). Given our allocation problem in which t_i cannot be altered, only reordered, we used permutation encoding. Data may be organized in one or two dimensions; common practice in allocation problems is to organize data in a matrix (Kolker, 2009), allowing organizing chromosomes in one or two dimensions (Tsai et al., 2015). The chromosome used in this study is comprised of a matrix $T_{m\times n}$ rewritten in one dimension (as a single row). Since our objective is to minimize the matrix sums of columns' variance, columns corresponding to each weekday are transposed and arranged sequentially, as shown in Fig. 1 with values exemplified from the current timetable (Table 1). Since $T_{m\times n}$ is a (33 × 10) matrix, the chromosome in Fig. 1 has 330 genes.

The initial population may be generated in different ways. A large number of chromosomes affects the algorithm's performance, whereas a small number limits the search space. The initial population may be entirely random or partially random, added of a solution already known, which may shorten processing time and enhance model performance (Marques et al., 2014). We tested two forms of initial population: totally random and partially random, added to the current timetable (Table 2).

Once the fitness function was defined and the initial population was generated, genetic operators of selection, crossover, and mutation were applied. We search for chromosomes with small variances. The selection used the linear rank selection (LRS), a method whose robustness has been demonstrated in several applications (Hussain & Muhammad, 2020). LRS ranks individuals according to their fitness value, assigning a survival probability proportional to their rank order. A roulette wheel sampling scheme is applied, in which individuals are assigned slices of a circular roulette wheel with slice size proportional to their fitness. Timetables with small variances are better ranked, displaying higher probabilities of being selected in the next step. The purpose of the crossover operation is to keep the best characteristics already present in the population, combining two chromosomes to obtain a better one in the next generation. We

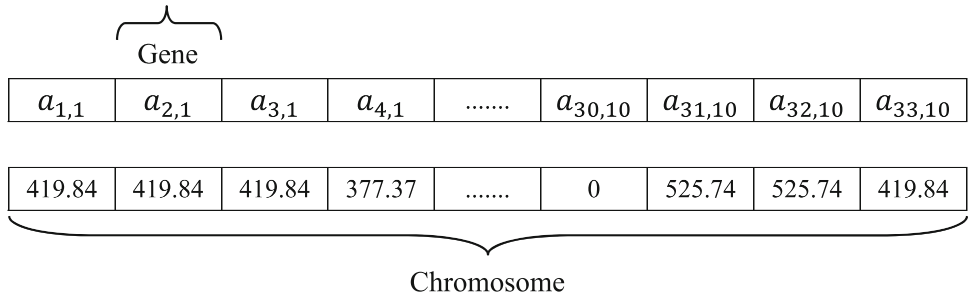

Fig. 1 Chromosome encoding using data from the current timetable

applied the Order Crossover (OX) technique, widely used in combinatorial problems and detailed in Arram and Ayob (2019). Mutation was carried out using the Simple Inversion Mutation (SIM), which randomly selects a subset of genes and then reattaches it to the chromosome in reversed order (Albayrak & Allahverdi, 2011).

Genetic operators' parameters were defined based on similar studies reported in the literature and considering the dataset at hand (Hussain & Muhammad, 2020; Kumar, 2013; Marchesi & Pacheco, 2016; Marques et al., 2014). We followed the method in Marques et al. (2014), which monitors the GA's performance while changing values of one parameter at a time. The following settings were applied: initial population of 100, 200, 400, and 1000; crossover rate of 0.7, 0.8, and 0.9; permutation rate of 0.1 and 0.2. We tested if the inclusion of the current timetable improved the GA performance. An elitism genetic operator was also considered and tested at three levels: no inclusion and inclusion at rates of 0.05 and 0.1. Two stopping criteria were considered for the GA: number of iterations (5000) or iterations with no improvement in the fitness function (1000). GA implementation was coded in R.

c. Step 3

The goal here is to determine the smallest number of changes to be implemented in the timetable obtained in Step 2 such that it resembles the current timetable (Table 1). For that, we define a path in which all specialties return to their original positions; such path orders changes, starting with those that promote the smallest increases in Eq. (1), generating a series of alternative timetables that start with the one given as the solution in Step 2 and end with the current timetable. To evaluate path progression, we used as indicator the number of identical time slots presented by a given timetable in the path and the current timetable; we denote it as Number of Matched Slots (NMS). NMS values vary from 30 [not 0, given restrictions for OR #2 in Eqs. (2) to (7)] to 330 (total number of assignable time slots in the table). An alignment heuristic is proposed to identify the path of alternative timetables.

Start by determining the value of indicator NUS (Number of Unmatched Slots) for the pair formed by the best solution from Step 2 (named Timetable I or T-I) and the Current Timetable (CT), and by identifying the unmatched slots in T-I. For unmatched slots to become matched, their corresponding surgical specialties need to be repositioned to their original assignments. Since specialties are allocated to more than one slot in CT, there is more than one option for them to return to their original assignments, and each option impacts differently the result in Eq. (1). To visualize possible changes, we create a directed network with nodes given by unmatched slots and edges oriented to indicate changes that would restore the specialty in the node to one of its original position in the current timetable. The weight assigned to edge (i, j) corresponds to the increase in Eq. (1) in case specialty i takes the slot occupied by specialty j, which would restore i to a time slot originally occupied in CT. The alignment heuristic that determines the path starts identifying the edge (i, j) with the smallest variance and swapping specialties i and j. Once the unmatched specialty in slot i is moved to the matched slot currently occupied by j, it leaves the network, which is then recalculated. In case a perfect swap takes place (i.e., both specialties i and j become matched slots), both nodes are removed from the network.

Figure 2 presents a network with 3 ORs working 5 days a week in 3 shifts. There are 4 unmatched slots (i.e., specialties) in the example, each corresponding to a node, and 6 directed edges connecting them, with corresponding variances (Var 1 to Var 6). Assume Var 1 to be the smallest variance; in that case, we would swap specialties MAS (Mastology) and THO (Thoracic). Since the edge is directed from MAS to THO, the swap would move MAS to a matched slot, but not THO. Thus, only node MAS would be deleted from the network, which would be updated. Considering the entire network of ORs, weekdays, and shifts, the process described in the example would be repeated until NMS = 330, and the current timetable is entirely restored. Note that at each iteration of the alignment heuristic, a new timetable is generated, such that NMS is increased by 1 and the value of z in Eq. (1) is updated. The progression of the path between T-I and CT is graphed with NMS positioned in the horizontal axis and the corresponding z value [Eq. (1)] in the vertical axis. The best compromise timetable may be determined visually or using an analytical approach, e.g., Jobson (1992, p. 377).

Table 3 Timetable I (T-I)

Room	Shift	Week 1					Week 2				
		Mon	Tue	Wed	Thu	Fri	Mon	Tue	Wed	Thu	Fri
1	*M*	PRI	PLA	THO	**URO***	PLA	PRI	**THO***	**GEN***	GEN	PLA
	A	PRI	**OTR***	THO	**URO***	**MAS***	PRI	**THO***	**GEN***	GEN	PLA
	E	PRI					PRI				
2	*M*	GEN	DIG		OBG	URO	GEN	DIG		OBG	URO
	A	PRI	PRI				PRI	PRI			
	E										
3	*M*	OBG	OBG	MAS	OBG	OBG	OBG	OBG	**OBG***	**ORT**	OBG
	A	**PRI***	*	**OBG***	OBG	**OTR***	OBG	OBG	**OBG***	**ORT**	OBG
	E										
4	*M*	VAS	ORT	ORT	ORT	NEU	**THO***	ORT	**GEN***	ORT	NEU
	A	ORT	ORT	ORT	ORT	NEU	**THO***	**MAS***	**GEN***	ORT	**DIG***
	E	PRI	ORT				PRI	**MAS***			
5	*M*	DIG	DIG	DIG	GEN	PRI	DIG	DIG	DIG	GEN	PRI
	A	**VAS***	DIG	GEN	GEN	PRI	DIG	DIG	GEN	**DIG**	PRI
	E					PRI					PRI
6	*M*	**NEU***	PRI	PED	VAS	PED	PED	PRI	URO	VAS	PED
	A	**NEU***	PRI	**PLA***	DIG	PRI	**DIG***	PRI	PED	PED	PRI
	E		PRI	**VAS***				PRI	PED		
7	*M*	**THO***	**OMF***	OTR	OTR	OTR	OTR	GEN	OTR	OTR	OTR
	A	*	OTR	OTR	OTR	OTR	OTR	OTR	**URO***	OTR	OTR
	E			**GEN***						**OTR**	
8	*M*	URO	URO	PRI	URO	URO	URO	**PRI***	PRI	URO	URO
	A	URO	**MAS***	PRI	PRI	URO	**THO***	*	PRI	PRI	URO
	E	URO		PRI	PRI		**THO***		PRI	PRI	
10	*M*	ORT	VAS	**URO***	GEN	**ORT***	**NEU***	**CRT***	DIG	**PLA**	URO
	A	VAS	ORT	**URO***	GEN	**ORT***	**NEU***	*	**URO***	**PLA**	**DIG***
	E	**CRT***	PRI	**PRI***	DIG	**ORT***	*	PRI		DIG	
11	*M*	CRT	DIG	CRT	**URO***	**GEN***	**PLA***	**PED***	**VAS***	CRT	**ORT***
	A	MAS	DIG	**OBG***	**URO***	**GEN***	*	**PED***	**VAS***	CRT	**ORT***
	E			**OBG***	**URO***	**GEN***				**OMF**	**PRI***
13	*M*	GEN	**PED***	NEU	**DIG***	VAS*	GEN	*	**URO***	ORT	VAS
	A	**ORT***	**PED***	PRI	**DIG***	**CRT***	**PRI***	NEU	PRI	PRI	VAS
	E		*	PRI	**PED***	**CRT***		NEU	*	**THO**	PRI

*: Unmatched slots with respect to current timetable

5 Results

The timetable currently used in the case study's surgical center is presented in Table 2. It yields an average daily demand of post-operative hours of ward bed of 11,218 h, with variance = 998,222 hours^2 (SD = 999 h). Minimum and maximum demands for hospital beds are 8,936 h (Thursday—Week 1) and 12,431 h (Monday—Weeks 1 and 2). Demand range is 3,495 h (which corresponds to 18.2% of the 19,200 daily hospital bed hours available in the hospital), and the coefficient of variation is 8.9%.

GA was implemented in R, version 4.1.0 (R Core Team, 2021), and the main packages used were tidyverse (Wickham et al., 2019) and GA (Scrucca, 2017). GA settings that generated the solution with smallest variance (T-I) were: initial population = 1000; crossover rate = 0.7; permutation rate = 0.2; elitism = 0.1; no inclusion of CT in the initial population.

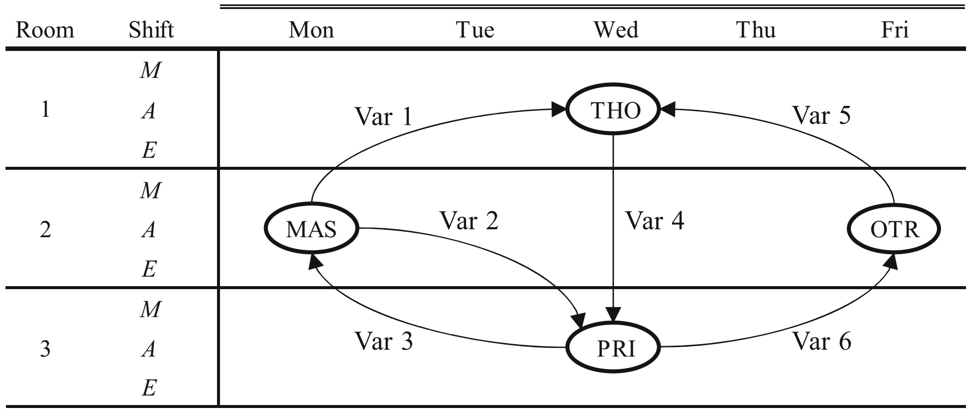

Fig. 2 Network depicting a surgical center with 3 ORs working 3 shifts during 5 weekdays

The processing time required to obtain the solution was 4 h and 2 min using a 2 × Xeon E5 2618L V3 processor, 64 Gb DDR4 RAM, SSD M.2 240 Gb NVME storage. Table 3 displays the allocations in T-I, which respected current demands for time slots by each specialty given in Table 2. T-I also kept the same number and positions of time slot allocations in OR #2 (reserved for robotics surgeries) within each specialty demanding that room. T-I yields an average daily demand of post-operative hours of hospital bed of 11,218 h, with variance = 12.3 hours2 (SD = 3.5 h). There is a 99.9% reduction in the variance of T-I in comparison with CT. Minimum and maximum demands reflect that decrease in variability; they are 11,214 h (Tuesday—Week 1 and Wednesday—Week 2) and 11,224 h (Friday—Week 1), respectively. Demand range in T-I is only 10 h (i.e., 0.05% of the total daily hours available in the hospital), and the coefficient of variation dropped to 0.03%.

T-I has 89 unmatched time slots if compared to CT. We applied the heuristic in Step 3 to find the minimum variance path from T-I to CT; its progression as a function of NUS and corresponding z values calculated using Eq. (1) is presented in Fig. 3. Variance remains very low from NMS = 241 to NMS = 320 when it starts to increase. Figure 3 confirms the good performance of the alignment heuristic and makes the choice of an alternative timetable straightforward. We chose the timetable corresponding to NMS = 320 (inflection point in the graph from which variance values only increase), denoted by T-II, to replace T-I as the best timetable for the case study's surgical center. T-II, displayed in Table 4, presents only 10 unmatched slots if compared to CT. It yields an average daily demand of post-operative hours of ward bed of 11,218 h, with a variance of 9,497 hours^2 (SD = 97.4 h), which implies a 99% reduction in variance compared to CT. Minimum and maximum demands are 10,987 h (Friday—Week 1 and Week 2) and 11,407 h (Monday—Week 1 and Week 2). The demand range is 420 h (i.e., 2.2% of the total daily hospital bed hours available in the hospital), and the coefficient of variation is 0.87%.

The method proposed in this paper generates several candidate timetables. The one resulting from applying the GA is suitable either for new surgical centers or for those showing more flexibility, usually owned by private hospitals. Intermediate timetables such as T-II are suitable for surgical centers such as the one investigated here that are already operating and accommodate small changes in time slots allocated to specialties. T-II provides a good balance between leveling bed demand over the planning horizon and minimizing the number of changes in the allocation of specialties.

Table 5 presents a summary of indicators measured at each timetable. Figure 4 displays the total post-operative bed demand (in hours) for the 10 weekdays covered in the timetable for each scenario (CT, T-I, and T-II). Dividing the total demand by 24, it is possible to estimate the daily demand for hospital beds. CT presents a demand that varies from 373 beds (Thursday, Week 1) to 518 beds (Mondays, Weeks 1 and 2), i.e., a range of 145. T-I presents the same demand (468 beds) in all ten days, while in T-II demand varies from 458 (Monday, Week 1) to 476 beds (Thursday, Week 2), i.e., an 18 range in demand.

5.1 Incorporating uncertainty through simulated scenarios

We devised a simulation experiment to assess the quality and stability of the deterministic solution proposed. The experiment would involve simulating scenarios where variations in both the length of stay (LOS) and the duration of surgeries were considered. For each specialty, scenarios would be generated by setting the LOS and surgery duration values to high and low levels, positioned at ± 3 standard deviations from the specialty's average values.

Given the impracticality of simulating scenarios for all 15 specialties in the current timetable, the simulation experiment focused on the Private surgical specialty. Despite being publicly funded, the hospital in our case study is allowed to rent 48 surgical time slots to private practices from any specialty.

Table 4 Timetable II (T-II)

		Week 1					Week 2				
Room	Shift	Mon	Tue	Wed	Thu	Fri	Mon	Tue	Wed	Thu	Fri
1	*M*	PRI	PLA	THO	**PED***	PLA	PRI	PLA	THO	GEN	PLA
	A	PRI	PLA	*	OMF	PLA	PRI	PLA	THO	GEN	PLA
	E	PRI					PRI				
2	*M*	GEN	DIG		OBG	URO	GEN	DIG		OBG	URO
	A	PRI	PRI				PRI	PRI			
	E										
3	*M*	OBG	OBG	MAS	OBG	OBG	OBG	OBG	MAS	OBG	OBG
	A	OBG	OBG	MAS	OBG	OBG	OBG	OBG	MAS	OBG	OBG
	E										
4	*M*	VAS	ORT	ORT	ORT	NEU	VAS	ORT	ORT	ORT	NEU
	A	ORT	ORT	ORT	ORT	NEU	ORT	ORT	ORT	ORT	NEU
	E	PRI	ORT				PRI	ORT			
5	*M*	DIG	DIG	DIG	GEN	PRI	DIG	DIG	DIG	GEN	PRI
	A	DIG	DIG	GEN	GEN	PRI	DIG	DIG	GEN	GEN	PRI
	E					PRI					PRI
6	*M*	**ORT***	PRI	PED	VAS	PED	PED	PRI	URO	VAS	PED
	A	**OTR***	PRI	PED	DIG	PRI	**OMF***	PRI	PED	PED	PRI
	E		PRI	PED				PRI	PED		
7	*M*	OTR	GEN	OTR	OTR	OTR	OTR	GEN	OTR	OTR	OTR
	A	OTR	OTR	OTR	OTR	OTR	OTR	OTR	OTR	**PED***	OTR
	E										
8	*M*	URO	URO	PRI	URO	URO	URO	URO	PRI	URO	URO
	A	URO	URO	PRI	PRI	URO	URO	URO	PRI	PRI	URO
	E	URO		PRI	PRI		URO		PRI	PRI	
10	*M*	ORT	VAS	DIG	GEN	URO	ORT	VAS	DIG	GEN	URO
	A	VAS	ORT	DIG	GEN	URO	VAS	ORT	DIG	GEN	URO
	E	URO	PRI		DIG		URO	PRI		DIG	
11	*M*	CRT	DIG	CRT	CRT	THO	CRT	DIG	CRT	CRT	THO
	A	**THO***	DIG	**MAS***	CRT	THO	MAS	DIG	THO	CRT	THO
	E										
13	*M*	GEN	GEN	NEU	**PED***	VAS	GEN	GEN	NEU	ORT	VAS
	A	GEN	NEU	PRI	PRI	VAS	GEN	NEU	PRI	PRI	VAS
	E	**THO***	NEU	PRI	PRI	PRI		NEU	PRI	PRI	PRI

*: Unmatched slots with respect to current timetable

In our method, the Private specialty's LOS values and surgery duration were determined using the historical participation percentage of all other surgical specialties in the timetable. Notably, the Private specialty has the largest allocation of time slots in the current timetable, comprising 48 or 20% of the total number of time slots, followed by Urology with 25 slots. By simulating scenarios for the Private specialty, we can effectively examine the effects of uncertainty in LOS and surgery duration values in a meaningful yet feasible manner.

Duration of surgeries and LOS values for the *Private* specialty followed a lognormal distribution. Therefore, values were log-transformed to calculate their respective 95%-confidence intervals and then reverse transformed to determine high and low variance levels, at $+/-3$ standard deviations from the averages. The levels tested in the simulation are given in Table 6. High and low levels are identified by $+1$ and -1, respectively.

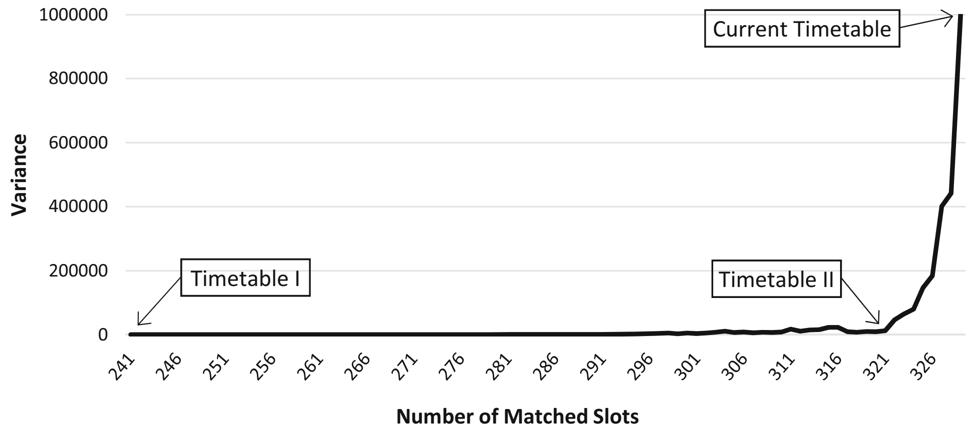

Fig. 3 Variance in post-operative demand for bed hours as a function of NMS in the timetable

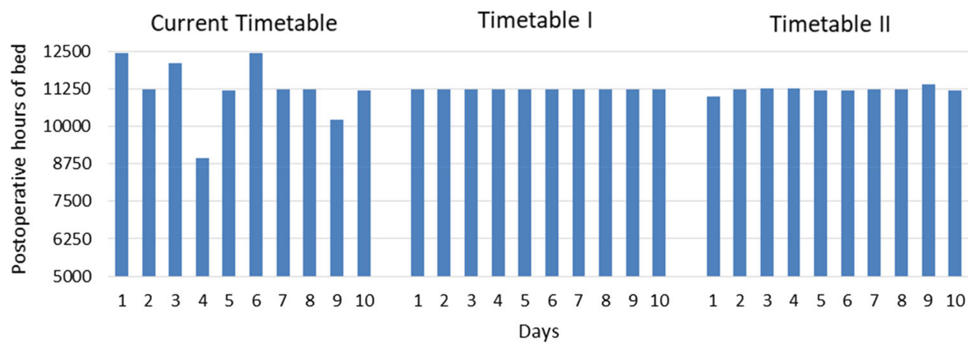

Fig. 4 Histogram of daily demand for post-operative bed hours in CT, T-I and T-II

Table 5 Comparison between CT, T-I and T-II

	Current timetable	Timetable I	Timetable II
Average	11,218	11,218	11,218
Standard deviation	999	3.5	97.4
Coefficient of variation	8.9%	0.03%	0.9%
Variance	998,222	12.3	9497
Minimum	8,936	11,214	10,987
Maximum	12,431	11,224	11,407
Range	3495	10	420

Table 6 Four scenarios in which surgery duration and ward bed demand are varied and corresponding index t_i

Scenario	Duration (h)	LOS (h)	t_i
− 1; − 1	3.20	221.31	414.97
− 1; + 1	3.20	228.41	428.29
+ 1; − 1	3.23	221.31	411.71
+ 1; + 1	3.23	228.41	424.93

Table 7 displays the optimal and best compromise solutions obtained for each scenario (labeled A to D) in the simulation experiment, along with those obtained using average duration and LOS values (Timetable II). Scenarios A to D correspond to compromise solutions positioned at inflection points in the graphs showing variance versus the number of matched slots (Fig. 5). The table presents the number of matched slots in each simulated scenario, along with objective function values and other pertinent statistics. Scenario B, characterized by low surgery duration and high LOS, notably impacts the t_i index, yielding a compromise solution with a high coefficient of variance in ward bed demands yet closely resembling the current timetable. The results from the remaining scenarios exhibit relatively similar outcomes. These experimental findings validate our decision to utilize average ward bed demand values in the proposed method.

6 Discussion and conclusion

The method proposed in this paper provides tools to surgical center managers to tactically plan the center's operation or revise its current operation. Although tailored to the specific needs of the surgical center in this case study, the steps can be adapted to other centers operating under similar circumstances. The method provides means to allocate surgical

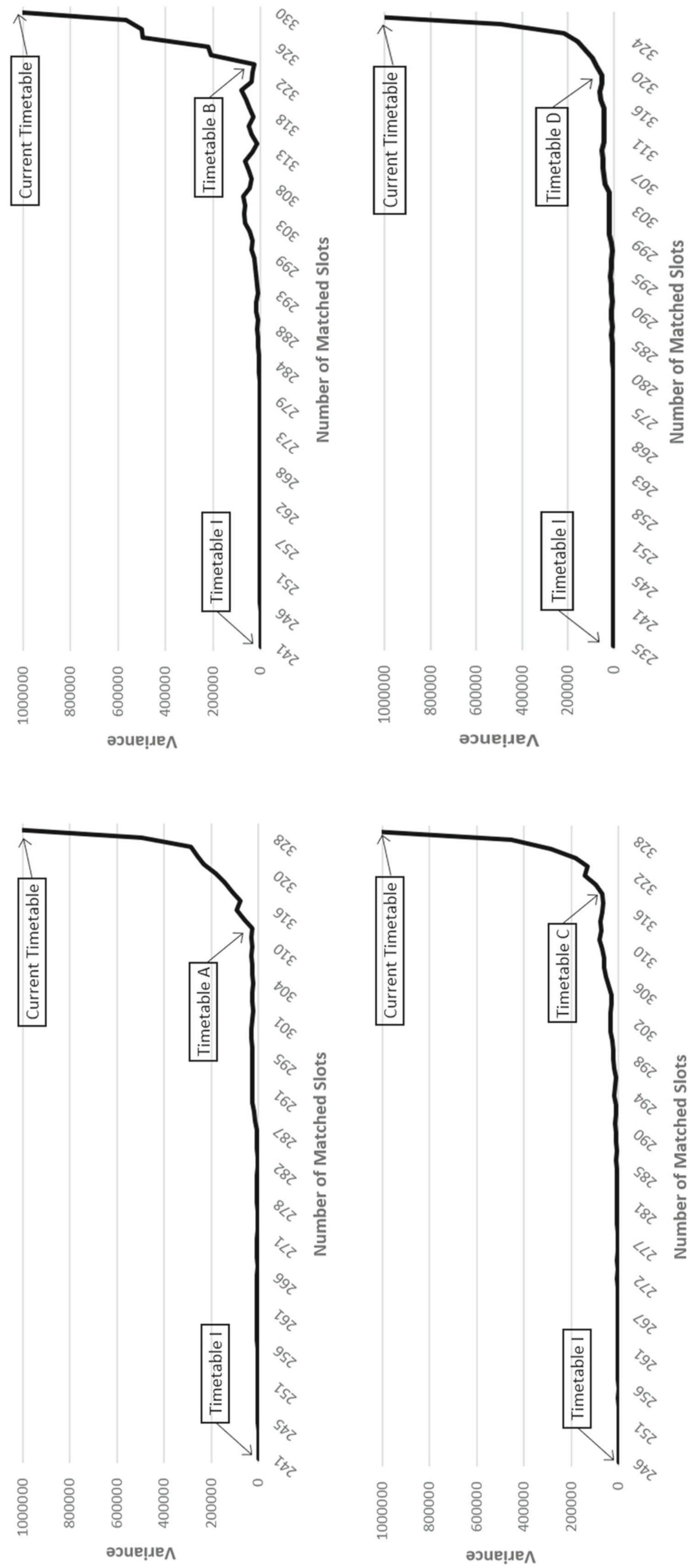

Fig. 5 Simulation results. Timetable I indicates the optimal solution for each scenario. Timetables A to D are the best compromise solutions for each scenario

specialties to OR time blocks in surgical centers with varying flexibility levels, which widens its applicability.

At a tactical level, MSS impacts directly on the variability in the daily demand for post-operative bed hours in hospital wards (Fügener et al., 2016), as well as other hospital sectors. There are several MSS optimization propositions in the literature, some of which address the MSS and SSP problems simultaneously. The analysis of long-term MSS schemes and proposition of alternative surgical timetables to those currently in use at hospitals face several practical barriers, e.g., difficulty of carrying out modifications in surgical centers under operation, hard-to-manage impacts foreseen in other hospital areas, and, most important, resistance from surgical teams to adopt changes in their daily schedules (Fügener et al., 2014). The method designed for this case study overcomes these barriers by proposing an alternative MSS close to the one currently in use.

Considering the current configuration of the timetable in the surgical center under analysis, preferences of some specialties for rooms and underutilization of the scheduled time were observed. It is well known that conflicting priorities and preferences of stakeholders are usual in surgery schedules (Cardoen et al., 2010a; Pandit & Tavare, 2011). Frequently, planning of these schedules is based on utilization: specialties that most use the OR time are given the convenience of blocks reserved for them, i.e., surgeons are treated as customers, and the best customers receive advantages (Wachtel & Dexter, 2008). However, literature is clear in that utilization should not be used to plan additional block time (Blake et al., 2002; Dexter et al., 1999). In addition to the equity in assignment among surgeons, minimization of hospital/staff costs and bed leveling are the most important criteria that should be addressed (Guerriero & Guido, 2011).

Additionally, in our case study, a large average and variance in daily demand for post-operative hours of hospital stay were observed. That derives from the way specialties are currently allocated to ORs. Reducing variability is mandatory since it could greatly improve efficiency (Harrison et al., 2005). Indeed, what happens inside the OR dramatically influences demands for resources downstream (Lin et al., 2013). For example, after surgery, the patient frequently occupies a bed and requires medical, nursing, and pharmaceutical assistance, as well as materials and equipment consumption; consequently, the demand patterns of those resources are dependent on the OR scheduling (Beliën et al., 2006; Su et al., 2011). If certain resources demanded are limited, and this is the classic example of beds in a hospital, OR time should be planned such that surgeons who use those resources will operate on different weekdays (Wachtel & Dexter, 2008). Block time for different surgeons should be planned to spread the workload evenly among days of the week: An example is the distribution of admissions to the intensive care unit more uniform on different days of the week after rearranging OR schedules (Kolker, 2009).

We analyzed the case of a static long-term surgical timetable, whose nature justifies the deterministic approach proposed. Authors who analyzed the MSS in similar scenarios either adopted the same approach (e.g., Bovim et al., 2020; Ma et al., 2013) or chose to disregard the impacts of block planning on the wards, not viewing bed availability as a constraint (e.g., Li et al., 2017; Testi et al., 2007). In opposition, the stochasticity of events derived from the OR operation was considered by most authors dealing with short-term MSS or tackling the MSS-SSP problems jointly (e.g., Adan et al., 2011; Pandit & Tavare, 2011). The SSP plan for the surgical center analyzed here, in which the stochasticity of events is considered, was reported in Calegari et al. (2020).

Our case study addresses the trade-off between achieving an alternative timetable that balances ward bed demand in the planning horizon while minimizing changes to the current timetable; however, this trade-off is not formally modeled. We employ a sequential approach where the optimal timetable is initially determined and then aligned with the timetable currently in use using a heuristic to seek a compromise solution that maintains balance in ward bed demand without major changes in specialties' allocation to timeslots. Similar approaches are found in several works dealing with the integration of tactical and operational levels of the ORSP (e.g., Agnetis et al., 2014). An integrated approach formally modeling and optimizing the trade-off could potentially yield improved results, as demonstrated in the literature. For instance, Gross et al. (2018) introduced a mixed-integer linear programming model to adjust duty and workstation rosters for physicians after unplanned absences, aiming to minimize disruptions while meeting regulatory and preference requirements, comparing results of sequential and integrated approaches. Wolbeck et al. (2020) addressed the nurse rescheduling problem by developing an optimization model that minimizes shift changes, ensuring smooth operation and nurse satisfaction, with demonstrated practical applicability in various real-world scenarios. Additionally, Wang et al. (2021) proposed a physician rescheduling model with capacity allocation for outpatients, considering non-stationary stochastic demand and adopting the Minimized Risk Tolerance Level criterion to mitigate capacity shortage risk for risk-averse hospital managers. Their study presented a bi-objective formulation to balance operational costs and capacity shortage risk, demonstrating the effectiveness of the model in managing the tradeoff.

In conclusion, it is possible to achieve a situation whereby surgical bed occupancy is planned with much less variability through modeling a new surgical center timetable. Planning and scheduling methods are needed to increase efficiency in surgical centers and consequently ward bed occupancy, as

Table 7 Original solution and simulation results. Timetables I denote the optimal solution in each case. Timetables II and A to D represent compromise solutions

	Original solution			Scenario A		Scenario B		Scenario C		Scenario D	
	Current timetable	Timetable I	Timetable II	Timetable I	Timetable A	Timetable I	Timetable B	Timetable I	Timetable C	Timetable I	Timetable D
Average	11,218	11,218	11,218	11,195	11,195	11,259	11,259	11,179	11,179	11,243	11,243
Standard Deviation	999	3.5	97.4	2.3	158.7	2.1	456.5	2.8	261.6	1.46	227.9
Coefficient of variation	8.9%	0.03%	0.9%	0.02%	1.4%	0.01%	4.0%	0.02%	2.3%	0.01%	2.0%
Variance	998,222	12.3	9,497	5.7	25,206	4.5	208,457	8.3	68,444	2.16	51,978
Minimum	8,936	11,214	10,987	11,192	10,905	11,257	10,320	11,175	10,771	11,241	10,854
Maximum	12,431	11,224	11,407	11,199	11,534	11,262	12,158	11,184	11,518	11,246	11,580
Range	3,495	10	420	7	629	5	1,838	9	747	5	726
Number of matched slots			320		313		325		320		320

every decision made at a given level influences those of the next one.

The main contribution of the method proposed here is producing alternative timetables that resemble the one currently in use at the hospital. Three aspects make that possible: First, the t_i index, which allows measuring the impact of different specialty assignments in other areas of the hospital; second, the NMS and NUS indicators, which enable measuring the impact of new specialty assignments in comparison with the existing timetable assignments; and third, the alignment heuristic, which reduces those impacts, increasing the model's applicability in real-life environments. The alignment heuristic produces different suboptimal alternative timetables that managers may analyze to choose the one that promotes acceptable changes in the specialty teams' schedules.

A great effort is needed to change the usual practice in healthcare institutions, as it is not clear to healthcare professionals the extent to which new ways of functioning would impact the care of patients, which is their usual concern. This is an important issue for further research: how to encourage units, their managers, and personnel to implement practices that clearly improve resource utilization. Changes in the hospital's MSS should jointly consider quantitative objectives as proposed here and subjective aspects, such as surgical teams' and individual preferences, which could be the object of future works. Exploring other surgical centers that implement long-term MSS could provide an interesting research avenue, further broadening the applicability of the method tailored for this particular case study. Finally, as mentioned above, the trade-off between balancing ward bed demand in the planning horizon while minimizing changes to the current timetable was not formally modeled and could be investigated as an extension of our research. One approach for that could use the Hilbert–Schmidt scalar product from the ACT method (Lavit et al., 1994) as objective function metric.

7 Data availability statement

The data that support the findings of this study are available from Hospital de Clinicas de Porto Alegre but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Data are, however, available from the authors upon reasonable request and with permission of Hospital de Clinicas de Porto Alegre.

Acknowledgements Not applicable.

Authors' contribution RC and FF wrote the main manuscript text, FL, JB and GY helped with the analyses, MA and GT developed the tables and figures, and BS thoroughly revised the entire manuscript.

Funding Not applicable.

Declarations

Conflict of interest All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript. Thus, the authors have no competing interests to declare that are relevant to the content of this article.

Ethics approval and consent to participate This research was approved by the Hospital de Clinicas de Porto Alegre (HCPA) Ethics Committee under project number CAAE 33705014.8.0000.5327, and the authors have complied with the recommendations of the Declaration of Helsinki. Data used in the method were extracted from the hospital's management system; patients' personal data were preserved.

Consent for publication Not applicable.

References

Abdalkareem, Z. A., Amir, A., Al-Betar, M. A., Ekhan, P., & Hammouri, A. I. (2021). Healthcare scheduling in optimization context: A review. *Health and Technology, 11*(3), 445–469. https://doi.org/10.1007/s12553-021-00547-5

Adan, I., Bekkers, J., Dellaert, N., Jeunet, J., & Vissers, J. (2011). Improving operational effectiveness of tactical master plans for emergency and elective patients under stochastic demand and capacitated resources. *European Journal of Operational Research, 213*(1), 290–308. https://doi.org/10.1016/j.ejor.2011.02.025

Agnetis, A., Coppi, A., Corsini, M., Dellino, G., Meloni, C., & Pranzo, M. (2014). A decomposition approach for the combined master surgical schedule and surgical case assignment problems. *Health Care Management Science, 17*, 49–59. https://doi.org/10.1007/s10729-013-9244-0

Akbarzadeh, B., Moslehi, G., Reisi-Nafchi, M., & Maenhout, B. (2020). A diving heuristic for planning and scheduling surgical cases in the operating room department with nurse re-rostering. *Journal of Scheduling, 23*(2), 265–288.

Albayrak, M., & Allahverdi, N. (2011). Development a new mutation operator to solve the traveling salesman problem by aid of genetic algorithms. *Expert Systems with Applications, 38*, 1313–1320. https://doi.org/10.1016/j.eswa.2010.07.006

Arram, A., & Ayob, M. (2019). A novel multi-parent order crossover in genetic algorithm for combinatorial optimization problems. *Computers and Industrial Engineering, 133*(March 2017), 267–274. https://doi.org/10.1016/j.cie.2019.05.012

Assad, D. B. N., & Spiegel, T. (2019). Maximizing the efficiency of residents operating room scheduling: a case study at a teaching hospital. *Production, 29*, e20190025.

Beliën, J., Demeulemeester, E., & Cardoen, B. (2006). Visualizing the demand for various resources as a function of the master surgery schedule: A case study. *Journal of Medical Systems, 30*(5), 343–350. https://doi.org/10.1007/s10916-006-9012-5

Beliën, J., Demeulemeester, E., & Cardoen, B. (2009). A decision support system for cyclic master surgery scheduling with multiple objectives. *Journal of Scheduling, 12*, 147. https://doi.org/10.1007/s10951-008-0086-4

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 and Analgesia, 94*, 143–148.

Bovim, T. R., Christiansen, M., Gullhav, A. N., Range, T. M., & Hellemo, L. (2020). Stochastic master surgery scheduling. *European Journal of Operational Research, 285*(2), 695–711.

Calegari, R., Fogliatto, F. S., Lucini, F. R., Anzanello, M. J., & Schaan, B. D. (2020). Surgery scheduling heuristic considering OR downstream and upstream facilities and resources. *BMC Health Services Research, 20*, 684. https://doi.org/10.1186/s12913-020-05555-1

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

Cardoen, B., Demeulemeester, E., & Van der Hoeven, J. (2010b). On the use of planning models in the operating theatre: Results of a survey in Flanders. *International Journal of Health Planning and Management, 25*, 400–414. https://doi.org/10.1002/hpm

Dexter, F., Macario, A., Traub, R. D., Hopwood, M., & Lubarsky, D. A. (1999). An operating room scheduling strategy to maximize the use of operating room block time: Computer simulation of patient scheduling and survey of patients' preferences for surgical waiting time. *Anesthesia and Analgesia, 89*, 7–20. https://doi.org/10.1097/00000539-199907000-00003

Fügener, A., Hans, E. W., Kolisch, R., Kortbeek, N., & Vanberkel, P. T. (2014). Master surgery scheduling with consideration of multiple downstream units. *European Journal of Operational Research, 239*, 227–236. https://doi.org/10.1016/j.ejor.2014.05.009

Fügener, A., Edenharter, G. M., Kiefer, P., Mayr, U., Schiele, J., Steiner, F., et al. (2016). Improving Intensive care unit and ward utilization by adapting master surgery schedules. *A & A Case Reports, 6*(6), 172–180. https://doi.org/10.1213/XAA.0000000000000247

Ghasemkhani, A., Tavakkoli-Moghaddam, R., Hamid, M., & Mahmoodjanloo, M. (2020). An improvement in master surgical scheduling using artificial neural network and fuzzy programming approach. In *IFIP international conference on advances in production management systems* (pp. 254–262). Springer, Cham.

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

Guido, R., & Conforti, D. (2017). A hybrid genetic approach for solving an integrated multi-objective operating room planning and scheduling problem. *Computers and Operations Research, 87*, 270–282. https://doi.org/10.1016/j.cor.2016.11.009

Gross, C. N., Fügener, A., & Brunner, J. O. (2018). Online rescheduling of physicians in hospitals. *Flexible Services and Manufacturing Journal, 30*, 296–328. https://doi.org/10.1007/s10696-016-9274-2

Hamid, M., Nasiri, M. M., Werner, F., Sheikhahmadi, F., & Zhalechian, M. (2019). Operating room scheduling by considering the decision-making styles of surgical team members: A comprehensive approach. *Computers and Operations Research, 108*, 166–181. https://doi.org/10.1016/j.cor.2019.04.010

Hans, E. W., Houdenhoven, M. V., & Hulshof, P. J. H. (2012). *A framework for healthcare planning and control* (pp. 303–320). Springer.

Hans, E. W., Wullink, G., van Houdenhoven, M., & Kazemier, G. (2008). Robust surgery loading. *European Journal of Operational Research, 185*(3), 1038–1050. https://doi.org/10.1016/j.ejor.2006.08.022

Harris, S., & Claudio, D. (2022). Current trends in operating room scheduling 2015 to 2020: A literature review. In *Operations research forum* (Vol. 3). Springer. https://doi.org/10.1007/s43069-022-00134-y

Harrison, G. W., Shafer, A., & Macky, M. (2005). Modelling variability in hospital bed occupancy. *Health Care Management Science, 8*, 325–334. https://doi.org/10.1007/s10729-005-4142-8

Heider, S., Schoenfelder, J., McRae, S., Koperna, T., & Brunner, J. O. (2020). Tactical scheduling of surgeries to level bed utilization in the intensive care unit. *IISE Transactions on Healthcare Systems Engineering, 10*(4), 229–242.

Hussain, A., & Muhammad, Y. S. (2020). Trade-off between exploration and exploitation with genetic algorithm using a novel selection operator. *Complex and Intelligent Systems, 6*(1), 1–14. https://doi.org/10.1007/s40747-019-0102-7

Jobson, J. (1992). *Applied multivariate data analysis, Vol. II—categorical and multivariate methods*. https://doi.org/10.1007/978-1-4612-0921-8

Kim, H. K., Ao, S. I., & Amouzegar, M. A. (2014). Operating room scheduling problems: A survey and a proposed solution framework. *Trans Eng Technol Spec Issue World Congr Eng Comput Sci*, 1–781. https://doi.org/10.1007/978-94-017-9115-1

Kolker, A. (2009). Process modeling of ICU patient flow: Effect of daily load leveling of elective surgeries on ICU diversion. *Journal of Medical Systems, 33*, 27–40. https://doi.org/10.1007/s10916-008-9161-9

Kumar, A. (2013). Encoding schemes in genetic algorithm. *International Journal of Advanced Research in IT and Engineering, 2*(3), 1–7.

Lavit, C., Escoufier, Y., Sabatier, R., & Traissac, P. (1994). The ACT (STATIS method). *Computational Statistics and Data Analysis, 18*, 97–119. https://doi.org/10.1016/0167-9473(94)90134-1

Li, X., Rafaliya, N., Baki, M. F., & Chaouch, B. A. (2017). Scheduling elective surgeries: The trade-off among bed capacity, waiting patients and operating room utilization using goal programming. *Health Care Management Science, 20*(1), 33–54. https://doi.org/10.1007/s10729-015-9334-2

Lin, Q. L., Liu, L., Liu, H. C., & Wang, D. J. (2013). Integrating hierarchical balanced scorecard with fuzzy linguistic for evaluating operating room performance in hospitals. *Expert Systems with Applications, 40*(6), 1917–1924. https://doi.org/10.1016/j.eswa.2012.10.007

Litvak, E., & Bisognano, M. (2011). More patients, less payment: Increasing hospital efficiency in the aftermath of health reform. *Health Affairs, 30*(1), 76–80. https://doi.org/10.1377/hlthaff.2010.1114

Ma, G., & Demeulemeester, E. (2013). A multilevel integrative approach to hospital case mix and capacity planning. *Computers and Operations Research, 40*(9), 2198–2207. https://doi.org/10.1016/j.cor.2012.01.013

Marchesi, J. F., & Pacheco, M. A. C. (2016). A genetic algorithm approach for the master surgical schedule problem. In *IEEE conference on evolving and adaptive intelligent systems* (pp. 17–21). https://doi.org/10.1109/EAIS.2016.7502366

Marques, I., Captivo, M. E., & Vaz Pato, M. (2014). Scheduling elective surgeries in a Portuguese hospital using a genetic heuristic. *Operations Research for Health Care, 3*(2), 59–72. https://doi.org/10.1016/j.orhc.2013.12.001

Marques, I., Captivo, M. E., & Barros, N. (2019). Optimizing the master surgery schedule in a private hospital. *Operations Research for Health Care, 20*, 11–24.

Martin, W. N., & Spears, W. M. (2001). *Foundations of Genetic Algorithms*. https://doi.org/10.1016/B978-1-55860-734-7.X5082-3

May, J. H., Spangler, W. E., Strum, D. P., & Vargas, L. (2011). The surgical scheduling problem: Current research and future opportunities. *Production and Operations Management, 20*(3), 392–405. https://doi.org/10.1111/j.1937-5956.2011.01221.x

McManus, M. L., Long, M. C., Cooper, A., Mandell, J., Berwick, D. M., Pagano, M., & Litvak, E. (2003). Variability in surgical caseload and access to intensive care services. *Anesthesiology, 98*(6), 1491–1496.

Melo, I. E. S., & Fogliatto, F. S. (2025). Integration of decision levels in operating room scheduling problems: Systematic review and proposition of a decision support framework. *Computers and Operations Research*. https://doi.org/10.1016/j.cor.2025.107063

Pandit, J. J., & Tavare, A. (2011). Using mean duration and variation of procedure times to plan a list of surgical operations to fit into the scheduled list time. *European Journal of Anaesthesiology, 28*(7), 493–501. https://doi.org/10.1097/EJA.0b013e3283446b9c

R Core Team (2021). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/

Roland, B., Di Martinelly, C., Riane, F., & Pochet, Y. (2010). Scheduling an operating theatre under human resource constraints. *Computers and Industrial Engineering, 58*(2), 212–220. https://doi.org/10.1016/j.cie.2009.01.005

Roshanaei, V., Booth, K. E., Aleman, D. M., Urbach, D. R., & Beck, J. C. (2020). Branch-and-check methods for multi-level operating room planning and scheduling. *International Journal of Production Economics, 220*, Article 107433.

Ryckman, F. C., Adler, E., Anneken, A. M., Bedinghaus, C. A., Clayton, P. J., Hays, K. R., et al. (2009). Cincinnati children's hospital medical center: Redesigning perioperative flow using operations management tools to improve access and safety. In E. Litvak (Ed.), *Managing patient flow in hospitals: Strategies and solutionsin hospitals* (2nd ed., p. 159). Joint Commission Resources.

Scrucca, L. (2017). On some extensions to GA package: Hybrid optimisation, parallelisation and islands evolution. *The R Journal, 9*(1), 187–206.

Spratt, B., & Kozan, E. (2016). Waiting list management through master surgical schedules: A case study. *Operations Research for Health Care, 10*, 49–64. https://doi.org/10.1016/j.orhc.2016.07.002

Su, M. C., Lai, S. C., Wang, P. C., Hsieh, Y. Z., & Lin, S. C. (2011). A SOMO-based approach to the operating room scheduling problem. *Expert Systems with Applications, 38*(12), 15447–15454. https://doi.org/10.1016/j.eswa.2011.06.016

Testi, A., & Tanfani, E. (2009). Tactical and operational decisions for operating room planning: Efficiency and welfare implications. *Health Care Management Science, 12*, 363–373. https://doi.org/10.1007/s10729-008-9093-4

Testi, A., Tanfani, E., & Torre, G. (2007). A three-phase approach for operating theatre schedules. *Health Care Management Science, 10*, 163–172. https://doi.org/10.1007/s10729-007-9011-1

Tsai, M. W., Hong, T. P., & Lin, W. T. (2015). A two-dimensional genetic algorithm and its application to aircraft scheduling problem. *Mathematical Problems in Engineering, 2015*, 2344. https://doi.org/10.1155/2015/906305

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*. https://doi.org/10.1007/s10729-012-9202-2

van Oostrum, J. M., Van Houdenhoven, M., Hurink, J. L., Hans, E. W., Wullink, G., & Kazemier, G. (2008). A master surgical scheduling approach for cyclic scheduling in operating room departments. *Or Spectrum, 30*, 355–374. https://doi.org/10.1007/s00291-006-0068-x

Wachtel, R. E., & Dexter, F. (2008). Tactical increases in operating room block time for capacity planning should not be based on utilization. *Anesthesia and Analgesia, 106*(1), 215–226. https://doi.org/10.1213/01.ane.0000289641.92927.b9

Wang, F., Zhang, C., Zhang, H., & Xu, L. (2021). Short-term physician rescheduling model with feature-driven demand for mental disorders outpatients. *Omega, 105*, Article 102519. https://doi.org/10.1016/j.omega.2021.102519

Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L. D. A., François, R., et al. (2019). Welcome to the tidyverse. *Journal of Open Source Software, 4*(43), 1686.

Wolbeck, L., Kliewer, N., & Marques, I. (2020). Fair shift change penalization scheme for nurse rescheduling problems. *European Journal of Operational Research, 284*, 1121–1135. https://doi.org/10.1016/j.ejor.2020.01.042

Zhu, S., Fan, W., Yang, S., Pei, J., & Pardalos, P. M. (2019). Operating room planning and surgical case scheduling: A review of literature. *Journal of Combinatorial Optimization, 37*, 757–805. https://doi.org/10.1007/s10878-018-0322-6

Authors and Affiliations

Rafael Calegari[1] · Flavio S. Fogliatto[1] · Filipe R. Lucini[2] · João B. G. Brito[1] · Gabrielli H. Yamashita[3] · Michel J. Anzanello[1] · Guilherme L. Tortorella[4,5] · Beatriz D. Schaan[6,7]

✉ Rafael Calegari
rafael.calegari@gmail.com

Flavio S. Fogliatto
ffogliatto@producao.ufrgs.br

Filipe R. Lucini
filipe.lucini@gmail.com

João B. G. Brito
joao.brito@ufrgs.br

Gabrielli H. Yamashita
gabrielli.hy@gmail.com

Michel J. Anzanello
anzanello@producao.ufrgs.br

Guilherme L. Tortorella
gtortorella@bol.com.br

Beatriz D. Schaan
bschaan@hcpa.edu.br

1 Department of Industrial Engineering, Universidade Federal do Rio Grande do Sul, Av. Osvaldo Aranha, 99, 5º Andar, Porto Alegre 90035-190, Brazil

2 Department of Critical Care Medicine, Cumming School of Medicine, University of Calgary, 3330 Hospital Dr NW, Calgary, AB T2N 4N1, Canada

3 Department of Production Engineering, Federal University of Ceará Campus do Pici, Block 735, Pici, Fortaleza, CE 60455-900, Brazil

4 Department of Mechanical Engineering, The University of Melbourne, Melbourne, Australia

5 IAE Business School, Universidad Austral, Buenos Aires, Argentina

6 Endocrine Division, Hospital de Clínicas de Porto Alegre, Av Ramiro Barcelos, 2350, 4º Andar, Porto Alegre 90035-903, Brazil

7 Department of Internal Medicine (Faculty of Medicine), Postgraduate Program in Medical Sciences: Endocrinology, Universidade Federal do Rio Grande do Sul, Porto Alegre, RS, Brazil