

Hospital Operating Room Scheduling and Staff Assignment

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Abstract

Operating rooms are among the costliest and busiest units in a hospital. California hospital data put one operating room minute at about 36 to 37 US dollars in 2014 and about 58 in 2022. This paper builds an optimisation model that schedules surgeries into rooms and days while respecting nurse and surgeon limits, minimising a weighted cost of opened room days, overtime, delayed surgeries and unscheduled surgeries. The model is solved with the CP-SAT solver in Google OR-Tools on synthetic instances of 10 to 100 surgeries. The 10 and 20 surgery cases were solved to proven optimality, while the 40, 70 and 100 surgery cases reached gaps of 2.8% to 6.7% within a 20 second limit. Four sensitivity tests varied session length, weekly demand, nurse availability and overtime cost. Extending sessions from 480 to 540 minutes cut cost by about 10%, and four rooms handled 55 surgeries a week but not 65. Surgeries were deferred at 8 nurses a day, all were scheduled at 10, and there was no firm gain above 12. A higher overtime cost removed almost all overtime with little effect on throughput. Because the data and costs are assumed, the results indicate how the system behaves rather than what a hospital would save.

Keywords: operating room scheduling; staff assignment; CP-SAT; sensitivity analysis; healthcare operations

1. Introduction

1.1 Background and Problem

Operating rooms are among the most capacity constrained resources in a hospital. An effective schedule must assign surgeries to rooms and days while respecting room time and the availability of clinical staff, and a schedule that uses room capacity well may still be infeasible if nursing capacity or surgeon availability is exceeded. Scheduling can therefore be posed as an Operations Research problem of allocating limited resources across competing surgical cases

(Cardoen et al., 2010; Al Amin et al., 2025a). The decision is more than maximising the number of surgeries performed: extra cases may need extra room days or overtime, while postponing or leaving out a surgery carries a penalty that depends on its priority (Al Amin et al., 2025a; Zhang et al., 2009).

This paper addresses an integrated operating room scheduling and staff capacity planning problem. The model decides which surgeries to schedule, on which day and in which room, subject to session capacity, allowable overtime, nursing capacity and surgeon workload, and it is tested from a small toy instance to a 100 surgery week (Wang et al., 2015; Roland et al., 2010; Breuer et al., 2020). The research problem is to find a cost efficient weekly schedule, and to use the formulation to assess how changes in room capacity, demand, nursing availability and overtime cost affect performance.

1.2 Research Questions and Objectives

1. How can surgical procedures be allocated across operating rooms and days while respecting room, nursing and surgeon capacity constraints?
2. How do session length, weekly surgical demand and nursing availability affect the proportion of surgeries that can be scheduled and the utilisation of hospital resources?
3. How does the cost assigned to overtime influence the trade-off between opening additional room days and using overtime capacity?

The objectives are to develop a model that minimizes a combined objective of room opening, overtime, waiting, and unscheduled surgery costs (Al Amin et al., 2025a; Zhang et al., 2009; Breuer et al., 2020), to provide a reproducible framework for analysis across demand and resource scenarios, and support managerial assessment of capacity trade-offs by means of sensitivity analysis.

1.3 Scope

The study is deterministic concerning the finite planning horizon, within which the hospital is scheduled to perform elective surgeries over several days. The study defines the surgeries by their duration, nursing requirement, priority, and surgeon. Rooms have a standard session and limited overtime, while staffing is described by aggregated nursing capacity and surgeon's daily limits (Cardoen et al., 2010; Al Amin et al., 2025a). Emergency arrivals and real time rescheduling, uncertain durations, downstream recovery bed or ICU capacity, individual nurse matching and rostering (Lim et al., 2016), equipment availability and setup dependent sequencing, and patient specific outcomes or hospital specific savings are outside the scope. These exclusions keep the formulation consistent with the implementation used in the experiments, whose data and costs are synthetic or assumed rather than observed (Breuer et al., 2020).

2. Literature Review

The literature on operating room (OR) scheduling is extensive. Cardoen et al. (2010) classified the papers based on the patient category, performance measure, decision level and solution method, while the reviews by Samudra et al. (2016), Zhu et al. (2019), Rahimi and Gandomi (2021) and Harris and Claudio (2022) discussed the achievements in the field, scheduling methods and recent trends, respectively. Al Amin et al. (2025a) grouped the papers according to the decision level and scheduling strategy (block, open and modified block). Their bibliometric analysis (Al Amin et al., 2025b) revealed that heuristics and integer programming were the methods used in the most widely cited papers, including the works by Guerriero and Guido (2011) and Hans et al. (2008), and identified uncertainty in surgery duration, staff availability and human factors as important factors to consider. The paper under review tackles the operational level scheduling decisions for a single period (a week). The assignment of surgery to rooms and days was addressed using a mathematical programming technique (Zhang et al., 2009), a pre-assignment heuristic (Tànfani and Testi, 2010), and a MIP model for constructing a daily schedule for a teaching hospital (Pulido et al., 2014). Tayyab et al. (2023) chose which rooms to open, where surgeries go and in what order while minimising overtime cost, a structure close to ours. Our model also follows an open strategy, in which any room can take any case, as in Fei et al. (2010) and Lin and Li (2021). Studies differ in how they handle priority and uncertainty (Min & Yih, 2010; Hans et al., 2008; Lamiri et al., 2008), and deterministic models remain a common first step, which this study adopts. The underlying problem is NP-

hard (Rahimi & Gandomi, 2021), as Lin and Li (2021) show by reduction to the 0–1 multiple knapsack problem, so exact solutions become harder as instances grow and solver time limits matter.

A room schedule can fail when staff are short, and many studies therefore add human resources. Roland et al. (2010), Beliën and Demeulemeester (2008) and Guo et al. (2016) integrate nurse and surgery scheduling, while Xiang et al. (2015) and Lim et al. (2016) bring in nurse rosters and lunch breaks. Breuer et al. (2020) and Bandi and Gupta (2020) link OR planning to personnel decisions, the former under uncertainty and the latter with a focus on staffing cost. Surgeon and crew limitations have been modeled as well (Meskens et al., 2013; Wang et al., 2015; Gür et al., 2023; Rath et al., 2017; Van Huele & Vanhoucke, 2014), and Aktas et al. (2024) that reviewed 29 studies claim that incorporating the surgical team brings important benefits. Most of these models operate at a level of individual staff and their rosters, adding realism but making these solutions harder to reproduce and convenient for answering questions about capacity at a fast rate.

On solution methods, MIP is the standard tool and constraint programming (CP) the main alternative. On a highly constrained daily theatre schedule, Wang et al. (2015) found MIP stronger with a weighted sum objective and CP stronger for makespan minimisation, and CP has also been applied to sequence dependent setup times and within branch-and-price-and-cut (Zhao & Li, 2014; HashemiDoulabi et al., 2016). Heuristics such as ant and bee colony methods scale well but offer no proof of optimality (Xiang et al., 2015; Lin & Li, 2021). CP-SAT, the open source solver in Google OR-Tools, combines CP search with SAT techniques and linear relaxations and reports either a proven optimum or an optimality gap at a time limit (Perron & Didier, n.d.; Perron et al., 2023). Its healthcare applications appear to have centred on nurse scheduling (Jiang et al., 2026; Demircioğlu & Mutlu, 2026), and in the sources reviewed we did not find one that assigns surgeries to room days under nursing and surgeon limits. Overtime is usually priced as a penalty that shapes the schedule (Lin & Li, 2021; Breuer et al., 2020; Tayyab et al., 2023), and work on over and underutilisation (Fügener et al., 2017; Wachtel & Dexter, 2008) supports treating capacity and overtime price as explicit decision levers. Cost inputs remain uncertain, since published per minute OR cost estimates vary widely and costs and charges are different measures (Macario, 2010; Childers & Maggard-Gibbons, 2018; Ashrafi et al., 2026), and surgery durations vary in practice (Costa, 2017). Section 7.2 therefore compares the assumed cost weights with published figures.

Three gaps appear to remain. Many staff aware models are detailed or rely on specialised heuristics, whereas this paper uses one open, transparent CP-SAT model with rooms, days, a daily nursing pool and surgeon limits. In the sources reviewed, few studies trace how the limiting resource moves as demand and staffing change, so we vary session length, weekly demand, nurse numbers and overtime cost to see when rooms and when nurses limit throughput. We also did not find a study that treats the overtime price as a lever and judges results against the solver's optimality gap, and here a sensitivity result is called firm only when it exceeds the combined solver gaps. Because the model is deterministic and uses synthetic data, these contributions concern system behaviour rather than hospital savings.

3. Mathematical Model Formulation

3.1 Model Overview

The formulation is a discrete optimisation model for operating room scheduling with staff capacity constraints. It assigns each surgery to at most one room and day, and decides which room days are opened and how much overtime is used. Staffing is modelled at capacity level: nursing requirements consume nurse minutes from a daily pool, and each surgery's surgeon has a daily operating limit, so individual nurse identities are not decision variables (Wang et al., 2015; Pulido et al., 2014). The model decides which room day each surgery goes to, not its start minute, which keeps it tractable but ignores skill mix, rosters and the timing of cases within a day. Models that assign individual nurses jointly with surgeries exist (Beliën & Demeulemeester, 2008; Guo et al., 2016), and a time sequenced variant is left for future work (Section 6.3).

3.2 Notation

Table 1. Sets, parameters (base case values) and decision variables

Symbol	Meaning
I, R, T, G	Sets of surgeries, operating rooms, planning days and surgeons, indexed by i, r, t, g
d_i	Duration of surgery i including a 30 minute turnover allowance; uses room and surgeon time
n_i ; p_i ; $g(i)$	Nurses required by surgery i (uses nurse minutes); its priority level (weights waiting and unscheduled penalties); its surgeon
H; OTmax	Standard session length per room day (480 min); maximum overtime per room day (60 min)
N; L^N ; L^G	Nurses available per day (14); nurse shift length (540 min); maximum operating minutes per surgeon per day (480 min)
C^R ; C^{OT}	Cost of opening a room day (300); cost of one overtime minute (2 in the base case)
C^W ; C^U	Waiting cost per priority point per delayed day (10); penalty per priority point for an unscheduled surgery (400)
x_{irt}	Binary: 1 if surgery i is scheduled in room r on day t
o_{rt}	Binary: 1 if room r is opened on day t
ot_{rt}	Integer, $0 \leq ot_{rt} \leq OTmax$: overtime minutes in room r on day t

3.3 Objective Function

The objective minimises room opening cost, overtime cost, priority weighted waiting cost and priority weighted penalties for surgeries left unscheduled (Al Amin et al., 2025a; Zhang et al., 2009; Tànfani & Testi, 2010):

$$\begin{aligned} \text{Min } Z = & C^R \sum_{r \in R} \sum_{t \in T} o_{rt} + C^{OT} \sum_{r \in R} \sum_{t \in T} ot_{rt} \\ & + C^W \sum_{i \in I} \sum_{r \in R} \sum_{t \in T} p_i \cdot t \cdot x_{irt} \\ & + C^U \sum_{i \in I} p_i (1 - D_i) \end{aligned}$$

Here $D_i = \sum_r \sum_t x_{irt}$ equals 1 if surgery i is scheduled and 0 otherwise, and $t = 0$ is the first planning day, so a surgery placed later accrues a larger priority weighted waiting cost. Higher priority surgeries receive a larger penalty when left out (Tànfani & Testi, 2010; Al Amin et al., 2025a).

3.4 Constraints

The seven constraints are listed in Table 2. Constraint 6 matters in practice, because concentrated surgeon workload can prevent surgeries from being scheduled even when rooms remain available (Roland et al., 2010; Zhang et al., 2009). In the implementation the objective is multiplied by 10 internally so that the overtime coefficient can be an integer, and reported objectives are converted back to the original scale.

Table 2. Model constraints

No.	Constraint	Meaning
1	$\sum_r \sum_t x_{irt} \leq 1 \quad \forall i$	Each surgery is scheduled at most once; a surgery may be left out and penalised instead
2	$\sum_i d_i x_{irt} \leq H o_{rt} + o_{rt} \quad \forall r, t$	Room time cannot exceed the standard session plus overtime
3	$o_{rt} \leq OT_{\max} o_{rt} \quad \forall r, t$	Overtime is possible only in an opened room, up to the cap
4	$x_{irt} \leq o_{rt} \quad \forall i, r, t$	A scheduled surgery requires an opened room day
5	$\sum_i \sum_r n_i d_i x_{irt} \leq N L^N \quad \forall t$	Nurse minutes needed on day t cannot exceed the daily nursing pool
6	$\sum_i g(i) = g \sum_r d_i x_{irt} \leq L^G \quad \forall g, t$	A surgeon's operating time per day is capped
7	$o_{rt} \geq o_{r+1,t} \quad \forall r, t$	Identical rooms are opened in index order, which removes symmetric solutions and helps the solver prove bounds

3.5 Assumptions

Surgery durations, the planning horizon and resource availability are known and deterministic. Each surgery has one surgeon with a limited daily workload, and nursing demand is the number of nurses required multiplied by duration, without modelling individual nurses (Lim et al., 2016). A room day must be opened before surgeries or overtime can be assigned to it, priorities are integer weights, and cost coefficients are assumed analytical weights rather than hospital financial data.

4. Data Sources and Methodology

4.1 Data and instance generation

Anonymised case level data that combine surgery duration, nursing requirement, surgeon assignment and urgency are rarely published openly, because they relate to patients and staff. Public repositories such as Kaggle and the UCI Machine Learning Repository host some surgical duration and hospital flow datasets, but none that we found contains all the fields the model needs. We therefore built structured synthetic instances, a common approach in the operating room scheduling literature (Cardoen et al., 2010; Samudra et al., 2016) that gives exact control of instance size and makes every result reproducible from a single random seed. Every instance is generated by one Python function (make_surgeries in or_experiments.py) with seed 7, using the rules in Table 3, and larger instances use the same function with more surgeries. Resource and cost values are those in Table 1.

All cost coefficients are assumed cost units, not hospital accounting data, because published estimates of the cost of operating room time vary widely (Childers & Maggard-Gibbons, 2018; Macario, 2010). The cost terms combine room opening, overtime, waiting and unscheduled surgery penalties, in line with objectives used in earlier work (Zhu et al., 2020). The results therefore indicate how the system behaves under different conditions and should not be read as predicted savings for a specific hospital.

Table 3. Surgery attributes

Attribute	Rule	Note
Duration	Base time drawn from {60, 90, 120, 150, 180, 240} min, scaled by a uniform factor between 0.9 and 1.1, rounded to 5 min, plus 30 min turnover	The duration range was selected to represent the substantial variation in elective surgical case lengths reported in operating room studies (e.g., Gómez-Díaz et al., 2017; Miller et al., 2023).
Nurses required	Drawn from {2, 3, 3, 4}	Mean 3; 3 is twice as likely
Priority	Uniform {1, 2, 3}	3 is the most urgent
Surgeon	Uniform over $\max(3, n/5)$ surgeons, where n is the number of surgeries	About 5 cases per surgeon per week

4.2 Solution method and experimental design

The model is implemented in Python 3.12 with the CP-SAT solver in Google OR-Tools 9.15 (Perron & Didier, n.d.; Perron et al., 2023). CP-SAT was chosen because it appears well suited to integer assignment models with side constraints and reports a proven lower bound, so each solution comes with a measure of its quality. Each run uses 8 search workers, solver seed 1 and a 20 second limit, and we report the optimality gap = (best objective – lower bound) / best objective, where zero means the schedule is proven optimal. Computation ran on a cloud Linux environment, and the script can be rerun on a standard laptop such as a Dell Inspiron 15 with an Intel Core i5 and 16 GB of RAM, although times and gaps may differ.

A scalability study solves five instance sizes (Toy 10 surgeries, 2 rooms, 2 days; Small 20/3/3; Medium 40/4/5; Large 70/5/5; Extra large 100/6/5). Four one at a time sensitivity tests then start from the Medium base case (40 surgeries, 4 rooms, 5 days, 14 nurses per day) and vary session length (360 to 600 min), weekly demand (25 to 65 surgeries), nurses per day (8 to 16) or overtime cost (0.5 to 20 per minute); the nurse and overtime tests use 55 surgeries to put the system under load. Each case is solved once, so differences smaller than the reported gap should not be read as real effects. For every run we record surgeries scheduled, room days opened, room use (surgery minutes divided by opened room days $\times 480$, above 100% when overtime is used), overtime, nurse use (nurse minutes in surgery divided by nurse minutes available), objective, gap and solve time.

The repository includes automated tests that check that the generator is reproducible and that the Toy and Small instances reproduce the proven optimal objectives in Table 4 (1740 and 2050), and all tables and figures regenerate with one command (python or_experiments.py). Solutions that stop at the time limit depend on the machine and thread scheduling, so small differences between runs are expected, while proven optimal solutions should reproduce exactly. The repository structure, tests and documentation were drafted with an AI coding assistant and then run and reviewed by the team.

5. Results

5.1 Scalability across instance sizes

Table 4 reports five instances ranging from a toy case to a hundred surgery week. The toy and small instances were solved to proven optimality in 0.04 and 5.2 seconds, whereas from the medium instance onward the solver stopped at the time limit with remaining optimality gaps of 2.8% for 40 surgeries, 5.2% for 70 and 6.7% for 100. The larger solutions therefore appear good, with a quantified gap, but are not proven optimal.

Table 4. Results by instance size

Instance	Surgeries	Room s x days	Schedule d	Room days opened	Room use (%)	Nurse use (%)	Overtime (min)	Objective	Gap (%)	Time (s)
Toy	10	2 x 2	8 (80%)	3	86.8	22.3	0	1740	0	0.04
Small	20	3 x 3	20 (100%)	6	100.7	36.4	20	2050	0	5.22
Medium	40	4 x 5	40 (100%)	13	99.5	51	40	4630	2.81	20
Large	70	5 x 5	70 (100%)	24	99.7	89.9	225	9290	5.21	20
Extra large	100	6 x 5	82 (82%)	29	92.6	98.3	15	19800	6.66	20.02

Room use is measured on the room days opened, and values above 100% appear because overtime minutes are counted against the 480 minute session. Nurse use is nurse minutes needed over nurse minutes available. The gap is the distance between the best solution and the solver's proven lower bound.

The toy instance schedules only 8 of 10 surgeries even though rooms are free, which appears to reflect surgeon availability: one surgeon holds 1,300 minutes of work across two days against a daily limit of 480 minutes. At the extra large scale, 82 of 100 surgeries are scheduled with 29 of 30 room days opened and nurse use at 98.3%, which suggests that rooms and nurses are both close to their limits.

5.2 Sensitivity analysis

Four one at a time sensitivity tests were run (Table 5, Figure 1). Because several runs end with a gap of 3% to 10%, differences of that size or smaller between neighbouring rows should not be read as real effects. Runs with identical settings (for example 55 surgeries, 14 nurses and an overtime cost of 2) come from separate runs and show 90, 235 and 110 overtime minutes at objectives within about 1% of each other, so overtime minutes should be read as indicative.

Session length. Session length was varied from 360 to 600 minutes with 40 surgeries. All surgeries were scheduled in every case, but the cost fell steadily: the objective fell by 27% when sessions grew from 360 to 480 minutes and by a further 18% at 600 minutes, while room days opened dropped from 17 to 11 and overtime from 175 to 5 minutes.

Demand. Weekly demand was raised from 25 to 65 surgeries on 4 rooms and 5 days. Up to 55 surgeries, everything is scheduled and overtime stays under 100 minutes, but the system appears to saturate at 65, where only 60 are scheduled and overtime rises from 90 to 655 minutes. The cost per scheduled surgery also climbs, from about 116 at 25 surgeries to about 136 at 55.

Nurse availability. With 55 surgeries requested, nurses per day were varied from 8 to 16. At 8 nurses only 46 surgeries (83.6%) are scheduled and nurse use is 96.4%, while raising the pool to 10 schedules all 55 and lowers the objective by 25%. Beyond 12 nurses the objective stays flat within the solver gap, so extra staff appears to add no measurable benefit in this setting.

Overtime cost. The overtime cost was varied from 0.5 to 20 per minute with 55 surgeries. At 0.5 per minute the model accepts 600 minutes of overtime to avoid opening extra rooms; at 2 per minute overtime falls to 110 minutes, and from 10 upward it is close to zero. Throughput is essentially unaffected, with 54 or 55 surgeries scheduled in every case.

Table 5. Sensitivity analysis results

Parameter	Value	Scheduled (%)	Room days opened	Overtime (min)	Nurse use (%)	Objective	Gap (%)
Session length (min)	360	100	17	175	51	6350	3.8
	420	100	15	45	51	5340	3.0
	480	100	13	45	51	4630	2.8
	540	100	12	10	51	4150	4.3
	600	100	11	5	51	3810	6.4
Weekly demand (surgeries)	25	100	9	0	31	2890	7.2
	35	100	13	25	46	4420	6.2
	45	100	16	85	58.8	5780	5.9
	55	100	20	90	70.6	7470	6.5
	65	92.3	20	655	79.5	10940	2.2
Nurses per day	8	83.6	16	55	96.4	10230	9.6
	10	100	19	250	98.9	7640	8.0
	12	100	19	195	82.4	7360	5.2
	14	100	19	235	70.6	7390	5.6
	16	100	19	200	61.8	7360	5.2
Overtime cost per minute	0.5	100	18	600	70.6	6880	3.1
	2	100	20	110	70.6	7470	6.6
	5	100	20	70	70.6	7760	10.1
	10	98.2	20	0	69.3	7670	9
	20	100	20	0	70.6	7460	6.4

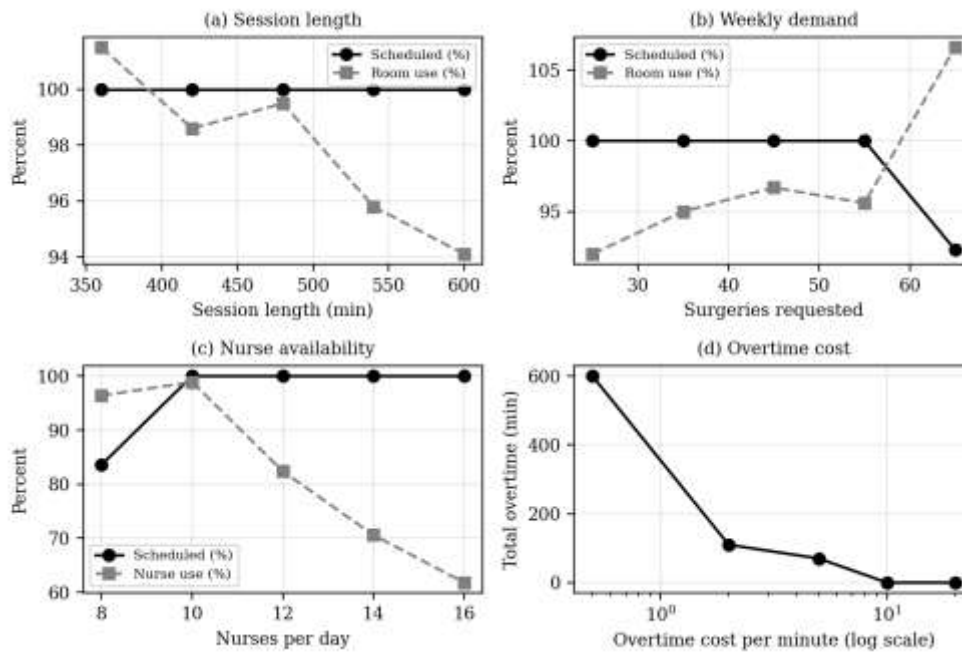


Figure 1. Sensitivity of throughput, utilisation and overtime to (a) session length, (b) weekly demand, (c) nurses per day and (d) overtime cost

6. Discussion and Managerial Implications

6.1 Main findings

The experiments suggest that the model finds good schedules quickly on small and medium weeks and that the limiting resource changes with the scenario. In the base case, rooms and session time appear to constrain the number of surgeries, with staffing also becoming a limiting factor during peak periods or insufficient staffing. At a capacity of 29 of 30 room days and 98% utilization of nurses, simultaneously reaching the limits for both resources, the number of surgeries was constrained by 18.

6.2 Implications for hospital decision makers

- Sessions might be increased before additional rooms are added. Increasing the length of each session by 60 min reduced the total cost by approximately 10% and freed up a room day in the base case, thereby reducing the capital expenditures, but this would require acceptance of longer working hours by the staff.
- The nursing resource seems to have a threshold character; below 10 nurses, the number of surgeries was limited by the insufficient staffing, but the addition of more than 12 nurses did not result in any increase in surgeries, so no benefits from their recruitment should be expected.
- The planning horizons should be designed to operate close to the saturation point (capacity). Four rooms processed 55 surgeries weekly at barely any overtime with little room for additional patients, but not 65.
- The overtime premium allows for a policy handle to reach the desired level of capacity utilization. With only a mild increase in average overtime costs, all overtime sessions were eliminated, freeing up additional capacity.
- The allocation of surgeons should be designed to avoid creating bottlenecks. In the toy example, two surgeries had to be postponed due to an uneven distribution of the surgical caseload between available surgeons.

6.3 Limitations and future work

The data are synthetic and the costs are assumed, so the results indicate how the system behaves rather than what a particular hospital would save. Larger instances were stopped at 20 seconds with gaps up to about 7% in the scalability runs and about 10% in the sensitivity runs, and the sensitivity tests changed one factor at a time, so interactions between factors were not tested. Real case mix and duration data would strengthen the analysis, and the model could be extended to emergency arrivals, uncertain surgery times and downstream recovery beds. A comparison of the exact model with a heuristic on the 100 surgery instances would also be informative.

7. Conclusion

7.1 Summary of findings

This paper asked how a hospital can schedule surgeries within nursing and surgeon capacity so that rooms are well used and high priority cases are not left waiting. One model for rooms, days, nursing capacity and surgeons (RQ1) produced good schedules on synthetic weeks of 10 to 100 surgeries within 20 seconds. The two smallest cases were proven optimal, and the 40, 70 and 100 surgery cases stopped with gaps of 2.8%, 5.2% and 6.7%, which is to be expected because assigning surgeries to room days under capacity limits contains bin packing as a special case. At 100 surgeries only 82 were scheduled, and nurse use reached 98.3% against 92.6% for rooms, which suggests that staffing was the tighter limit (Table 4).

The sensitivity tests address RQ2 and RQ3 (Table 6). Longer sessions lowered cost, with the move from 480 to 540 minutes saving about 10%. Four rooms coped with 55 surgeries a week but not 65, where total cost rose by about 46% and 5 requests went unscheduled. Nurses appeared to act as a threshold, with surgeries deferred at 8 nurses a day and no firm gain beyond 12. Because the overtime price changed overtime minutes far more than total cost, it seems to work as a dial between opening rooms and using overtime.

Table 6. Summary of the four levers (from Table 5)

Lever	Change	Main effect	Cost change	Firm?
Session length	360 to 480 min	Room days 17 to 13; overtime 175 to 45 min	-27.1%	Yes
Session length	480 to 540 min	Room days 13 to 12	-10.4%	Yes
Session length	480 to 600 min	Room days 13 to 11; overtime 45 to 5 min	-17.7%	Yes
Nurses per day	8 to 10	Scheduled 83.6% to 100%	-25.3%	Yes
Nurses per day	12 to 16	Scheduled 100% in both cases	0.0%	No
Weekly demand	55 to 65 surgeries	Scheduled 100% to 92.3%; overtime 90 to 655 min	+46.5%	Yes
Overtime cost	0.5 to 2 per min	Overtime 600 to 110 min; room days 18 to 20	+8.6%	No
Overtime cost	2 to 10 per min	Overtime 110 to 0 min; scheduled 100% to 98.2%	+2.7%	No

A cost change is firm when it is larger than the two solver gaps combined. The overtime cost acts mainly on overtime minutes, not on total cost.

7.2 Link to published evidence

Our model is developed within a well-researched area, as the literature includes relevant studies which highlight potential improvement sites (Cardoen et al., 2010; Zhu et al., 2019). Researchers have proposed various approaches to address the scheduling problem in question. For instance, Beliën and Demeulemeester (2008) integrated the scheduling of nurses and surgeries by employing a branch-and-price algorithm, whereas Gür et al. (2023) utilized the constraint programming framework, to which Google's OR-Tools CP-SAT solver belongs, with goal programming to first assign surgical teams to procedures and then schedule surgeries in operating rooms. According to the review article published in 2024, involving the analysis of 29 studies, the surgical team is a critical addition to the scheduling model as it offers substantial benefits (Aktas et al., 2024). Thus, our study is a small-scale experiment which adds to the series of research works on operating room scheduling and contributes to the evidence base that the resource limitation shifts from operating rooms to nurses depending on the demand and availability figures.

Our costs are assumed units, so we compared them with published figures. California hospital data give an operating room cost of 37.45 US dollars per minute for inpatient cases and 36.14 for ambulatory cases in fiscal year 2014 (Childers & Maggard-Gibbons, 2018), and about 58 dollars in fiscal year 2022 (Ashrafi et al., 2026). A 2005 study of 100 US hospitals, reported in Macario (2010), found average charges of 62 dollars per minute, with a range of 22 to 133. Charges and costs are different measures and should not be mixed (Ashrafi et al., 2026).

The model charges 300 for a room day and 2 for an overtime minute. If the room day cost stands for a full 480 minute session, one room minute costs 0.625, and an overtime minute priced the same way would also cost 0.625. Suppose overtime labour is paid at 1.5 times the normal rate, which is an assumption. Wages and benefits are about 13 to 14 of the 36 to 37 dollars, roughly 37% of cost (Childers & Maggard-Gibbons, 2018), and only this labour share rises, so the overtime price becomes about $0.625 \times (1 + 0.5 \times 0.37) \approx 0.75$. Both values lie close to the lowest price that we tested (0.5) and below the base value (2). At the level of 0.5 the model accepted 600 minutes of overtime and opened 18 room days instead of 20 (Table 5), so the base case may underestimate how much overtime a cost minded hospital would accept. We need real cost data to settle this.

7.3 Final remark

The data are synthetic and the costs hypothetical, so the results describe system behaviour rather than hospital gains (Section 6.3 lists further limitations). However, a single model of CP-SAT can yield useful weekly operating room schedules, and it indicates where one should focus in planning effort: longer sessions before new rooms, nurse staffing above a threshold and a price on overtime.

Declarations

Conflict of interest: The authors declare no conflict of interest.

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