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Multi-surgeon and priority-aware scheduling for operating rooms scheduling: a robust-based approach

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ABSTRACT

In the realm of medical centre operations, Operating Room (OR) departments emerge as pivotal entities, given their substantial financial and social implications. A fundamental aspect of OR theatre management pertains to advance scheduling. Within this research, a novel robust-based modelling approach is developed to formulate the Operating Room Scheduling (ORS) under an open scheduling strategy, considering both the most optimistic and pessimistic scenarios for surgeries. This approach ensures that the total duration of surgeries in an OR adheres to both standard and the maximum allowable working hours, even when surgeries extend to their best-case and worst-case durations on a given day. Furthermore, the model accommodates surgeries involving multiple surgeons from diverse specialties. To minimise the cancellation rate of critical patient operations, the prioritisation of vital patients in the sequence of daily operations is incorporated. The study employs an efficient solution approach combining the use of Lagrangian Relaxation to derive relaxations, and Valid Inequalities (VIs) to strengthen the quality of relaxation. This approach aims to enhance computational efficiency and reduce processing time for the proposed model. To validate its practicality and effectiveness, the model is applied to a real-world case study. The research also encompasses sensitivity analyses, offering valuable managerial insights.

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1. Introduction

The healthcare sector is a fundamental component of all economies, as healthcare system expenditures and revenues play a pivotal role in economic dynamics (Ghasemi et al., 2023). Beyond its economic impact, the efficiency of healthcare delivery, comprising technical efficiency (optimal resource utilisation), production efficiency (cost-effectiveness in service delivery), and equity (fair access to surgical services), is crucial in ensuring sustainable and high-quality healthcare systems. Hospitals, as the central entities within the healthcare system, not only contribute to economic activity but also influence patient health outcomes and overall well-being (Goodarzian et al., 2023). Among hospital resources, operating rooms (ORs) are particularly noteworthy, as they account for approximately 33 percent of expenses and generate around 66 percent of profits, highlighting their role in both financial sustainability and operational efficiency (Kayvanfar et al., 2021). Effective OR management is essential for balancing cost control with patient-centred care, as delays or inefficiencies in OR scheduling can negatively impact surgical quality, waiting times, and patient satisfaction. The planning of ORs can be categorised into three distinct levels, each serving a unique purpose. The strategic level primarily encompasses long-term planning decisions, ensuring resource allocation aligns with both financial sustainability and healthcare demand. At the tactical level, the focus shifts to the master scheduling of surgeries, which involves the pre-assignment of ORs to specific surgeons or specialties to optimise operational workflow and service efficiency. Finally, the operational level is where advance scheduling and allocation scheduling are executed, ensuring the smooth and efficient functioning of ORs while minimising patient wait times and maximising surgical throughput (Zhu et al., 2019). Proper OR management leads to improved OR

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utilisation, enhanced surgical care quality, better health outcomes, and patient satisfaction, while also reducing operational costs (Tsang et al., 2025).

In the realm of operating room scheduling (ORS), one of the most intricate challenges pertains to the inherent uncertainty surrounding the durations of surgical procedures, which can only be estimated with limited precision. When surgeries exceed their anticipated durations, it has a cascading effect, potentially leading to additional costs when scheduling extends beyond the normal operating hours of the facilities (Abdeljaouad et al., 2020). Furthermore, as outlined by Zhu et al. (2019), uncertainties in the surgical department encompass a broader spectrum, spanning aspects such as patient arrivals, resource availability, and specific care requirements. Extensive scholarly attention has been devoted to the investigation of uncertainties within the OR department (Barrera et al., 2020). However, it is notable that a significant portion of these studies has predominantly relied on conventional and widely recognised methods, such as the robust approach pioneered by Bertsimas and Sim (2004), to address and manage this inherent uncertainty.

Furthermore, the presence of surgeries necessitating the participation of multiple surgeons, as noted by Molina-Pariente et al. (2015), introduces a distinctive complexity to the field of ORS. Addressing these complex surgical scenarios in ORS is a formidable undertaking, yet it holds the potential to significantly enhance the practicality and real-world applicability of scheduling processes. It is noteworthy that, despite their evident relevance, the literature on ORS has not thoroughly explored such multifaceted surgeries.

In the literature of ORS, there are two main scheduling strategies: block scheduling, where the OR schedule is divided into blocks that are given to different specialisations; and open scheduling, where appointments can be scheduled in any OR. The former is less complicated, but the latter, despite its complexity, is more flexible and efficient in the management of ORS (Al Amin et al., 2025).

Within the scope of this research, a novel open strategy ORS problem is formulated for elective patients, employing binary programming techniques. This approach adeptly manages the inherent uncertainty associated with surgical durations, ensuring that the scheduling minimises the detriment to critical patients while also guaranteeing that the total surgical time remains within the constraints of the maximum allowable working hours. Moreover, the model accommodates the intricacies of surgeries involving multiple surgeons with diverse specialties, a vital consideration in the proposed framework. A distinctive feature of this study is the prioritisation of vital patients by scheduling their procedures at the outset of each day in the ORs. This strategic approach is designed to mitigate the risk of cancellations resulting from the unforeseen prolongation of preceding surgeries, a dimension that has not been sufficiently addressed in the existing literature.

This research endeavour seeks to address the following pivotal inquiries as research questions (RQs):

(1) How can the Operating Room (OR) schedule be robust to withstand the unpredictability of surgery durations?
(2) What strategies can be employed to effectively manage the urgency of patients' medical conditions (patients' priority) within the framework of Operating Room Scheduling (ORS) on the day of surgery?
(3) What innovative approaches can be adopted to encompass surgeries requiring the participation of multiple surgeons in the ORS problem formulation?

This research offers a set of significant contributions to the field, which encompass:

- The formulation of a novel robust approach is designed to effectively manage the inherent unpredictability of surgical procedure durations considering the optimistic and pessimistic scenarios for surgery durations.
- The implementation of a strategic prioritisation strategy, with a focus on vital surgeries scheduled at the outset of each day, aimed at mitigating the risk of cancellations for patients with urgent medical needs.
- Inclusion of a comprehensive treatment of special surgeries necessitating the involvement of multiple surgeons with diverse specialties.

This section serves as an introductory segment, outlining the significance of the subject matter and providing a concise overview of the research approach employed. The subsequent sections of this paper are structured as follows: In Section 2, we delve into an extensive review of existing literature on ORS, with a particular focus on studies that incorporate uncertain parameters within their optimisation models. This review process aims to identify and elucidate any gaps in the existing body of research. Section 3 is dedicated to elucidating the methodology underpinning this study, including the formulation of the mathematical model devised to address the research gap identified in Section 2. The practical applicability and validation of the proposed model are scrutinised in Section 4 through its application to a real-world case study. Section 5 provides an in-depth exploration of sensitivity analyses and offers insights of managerial relevance. Finally, Section 6 offers a conclusion summarising the findings and suggests potential avenues for future research in this domain.

2. Literature review

This section offers a comprehensive literature review, which is divided into three distinct sub-sections for clarity and coherence. The review process commences by categorising papers pertaining to ORS into two primary domains, each based on the nature of uncertainty they address. The initial sub-section presents a synthesis of ORS research that specifically delves into the problem with stochastic uncertain parameters, offering insights and findings from these studies. Subsequently, the second sub-section explores ORS papers focusing on non-stochastic uncertainty, elucidating the key takeaways and contributions of these investigations. It should be noted that Al Amin et al. (2025) reviewed the papers in the field of ORS and optimisation that is enhanced in the review of this research specifically with a focus on uncertainty in ORS. Ultimately, the section culminates in an exploration of the research landscape, identifying any discernible gaps or areas where additional scholarly attention may be warranted.

2.1. ORS with stochastic uncertainty

Razmi et al. (2015) have contributed significantly to the realm of healthcare management, particularly in the context of operating theatre operations. They presented a model for ORS, where the primary constraint centred around the use of unique equipment. Their approach unfolded in three stages: initially, they addressed elective patient scheduling, taking into consideration the uncertainty related to the utilisation of unique equipment. Subsequently, they extended their model to accommodate emergency patients. Finally, the model introduced a coefficient factor to account for surgeon-specific considerations when employing this specialised equipment. In a parallel vein, Kamran et al. (2018) delved into the intricacies of Advance Scheduling Problems, wherein patients from a waiting list needed to be judiciously selected and allocated to available OR blocks within a short-term schedule, all the while navigating a myriad of constraints. They derived the availability of blocks through a modified block scheduling strategy and introduced multiple objectives encompassing the minimisation of patient waiting times, tardiness, cancellations, block overruns, and the optimisation of surgery days for individual surgeons within the planning horizon. To grapple with the intricacies of uncertainty, they introduced stochastic surgery durations, examining the problem from the vantage point of both two-stage stochastic and two-stage chance-constrained stochastic formulations. In a similar vein, Abdeljaouad et al. (2020) directed their focus towards the scheduling of surgeries within an operating theatre environment. Their challenge involved organising a set of operations, all slated for identical ORs, each with uncertain durations and necessitating pre- and post-surgery setup activities. Their central objective was to determine the optimal sequence of operations within each OR, with an eye toward minimising the overall theatre's opening duration and surgeons' waiting times. To address this complex problem, they devised a stochastic simulated annealing-based algorithm, representing the inherent uncertainty through the Stochastic Approximation Algorithm (SAA) technique. Rahmani Manshadi (2024) developed a robust mixed-integer binary programming model aimed at optimising ORS in stand-alone cardiac hospitals. Their goal was simultaneously optimising three objectives: maximising resource efficiency, reducing patient waiting times, and minimising surgical costs. To accomplish this, the study employed the augmented epsilon constraint method for multi-objective optimisation. The proposed framework not only assigns ORs to both patients and surgeons but also determines the necessary bed capacity in downstream units, ensuring a well-coordinated and efficient hospital workflow. Azab et al. (2025) studied the ORS model in a bi-objective area under uncertainty. In their study, they took into account collaborative surgeries as well as surgeons' preferences and tried to minimise operating costs and maximise surgeons' preferences simultaneously, followed by presenting a balanced solution for medical staff and the management of the hospital. After proposing a MILP model, they used the SAA method to handle their problem.

Mazloumian et al. (2022) ventured into the domain of multi-objective integer linear programming, where they endeavoured to integrate OR planning and advanced scheduling within a surgery department encompassing various specialties. Their work grappled with the allocation of surgical specialties to OR blocks and the assignment of patients from each specialty's waiting list to these blocks. In this intricate landscape, uncertainty surrounding surgery durations and the influx of emergency cases added layers of complexity. The focal objectives were twofold: enhancing service quality and operational efficiency. Their approach leveraged the LP-metric to optimise the integrated objective function, and they fortified the model's robustness by adopting a transformation framework. Lastly, Maleki et al. (2023) introduced a multi-stage Mixed Integer Programming (MIP) framework for optimising both operation times and resource allocation. Their innovative approach hinged on the use of a decision tree methodology to address uncertainties encountered at each level of the decision-making process. This entailed considering optimistic, most probable, and pessimistic scenarios, followed by the application of robust optimisation and Upper Partial Moments techniques to derive efficient solutions under varying conditions of uncertainty. Almoghrabi and Sagnol (2025) studied the elective surgery planning problem in a hospital with ORs shared by elective and emergency patients. Their problem was split into two phases, where, first, a subset of patients who are going to be operated on in the planning period are selected and assigned to a block and a tentative starting time. In the second phase, a policy decides how to insert emergency patients into the schedule and may cancel planned surgeries.

2.2. ORS with non-stochastic uncertainty

Several scholars have made substantial contributions to the domain of ORS, addressing a multitude of complex challenges arising from uncertainties and resource allocation. These research endeavours encompass a broad spectrum of methodologies and objectives.

Addis et al. (2016) navigated the task of selecting a cohort of patients from an elective patient waiting list and meticulously assigning them to a predefined set of available OR blocks. Their work was underpinned by a block scheduling strategy, involving a stipulated number of blocks with given durations. Importantly, each patient in this context was characterised by both a recommended maximum waiting time and an inherently uncertain surgery duration. Marques and Captivo (2017) introduced a thoughtful approach aimed at assisting surgical planners in optimising the utilisation of available surgical resources. Their multi-objective modelling spanned three distinct versions, representing a spectrum from the administration's intentions to the surgeons' current practices. They also incorporated a midway approach, mirroring negotiations with surgeons. In response to the challenge of uncertain surgery durations, they advocated a robust approach to enhance decision-making in this context. Neyshabouri and Berg (2017) ventured into the domain of two-stage robust modelling, focusing on the intricate landscape of uncertainty surrounding surgery durations and the length of stay in surgical ICUs. Their methodology allowed decision-makers to flexibly adjust the level of risk, enhancing the adaptability of their approach. A noteworthy component of their research was the introduction of an adapted column-and-constraint generation technique for the attainment of exact solutions.

Vali-Siar et al. (2018) embarked on an exploration of the multi-period and multi-resource challenges associated with integrated OR planning and scheduling, all within a backdrop of uncertainty. Their efforts culminated in the development of a MIP model aimed at minimising tardiness in surgeries, overtime, and idle time. Notably, the duration of surgeries and recoveries was subject to uncertainty, which they adeptly addressed through the application of a robust optimisation approach. Wang et al. (2019) turned their focus to the intricacies of surgery block allocation, aiming to optimise OR usage by determining the appropriate ORs to open and the assignment of surgeries from a daily listing, all while minimising the associated OR opening and overtime penalty costs. They introduced an ambiguity set of distribution, incorporating empirical means, mean absolute deviations, and the support set to address the uncertainties at play.

Breuer et al. (2020) charted an innovative path by developing a robust optimisation model that seamlessly integrated staffing and scheduling decisions. Their aim was to mitigate foreseeable variations in operation durations, staff availability, and emergency patient arrivals, ensuring greater resilience in the face of uncertainty. Shehadeh and Padman (2021) focused on the complex decision-making process of assigning elective patients to available surgical blocks in multiple ORs, all against the backdrop of random surgery durations and postoperative ICU sojourns. They introduced a distributionally robust elective OR scheduling model, seeking to minimise the costs associated with both performing and postponing surgeries, all while navigating the uncertainties posed by ambiguous probability distributions. Azar et al. (2022) introduced a time-indexed scheduling formulation to address the ORS problem. They notably proposed the incorporation of chance constraints linked to the probability distribution of surgery durations to enhance scheduling performance, demonstrating the advantages of implementing such constraints as linear entities. Finally, Dai et al. (2023) grappled with a fuzzy surgery scheduling problem riddled with uncertainty, particularly in the context of an epidemic. Their innovative algorithm was designed to minimise various costs, including operating room overtime, bed shortages, and patient waiting times. Leveraging a combination of differential evolution and heuristic rules, their algorithm offered an effective solution to the multifaceted problem at hand. Fallahpour et al. (2024) investigated the intricacies of integrated OR planning and scheduling, focusing on elective and emergency patients in an uncertain environment. They developed a mixed integer programming framework to minimise inactivity and patient wait times while optimising high-priority resource allocation. Both upstream and downstream units of the ward were included. A robust optimisation strategy is harnessed to effectively grapple with the uncertain aspects of surgery, including surgical duration, length of stay, and the influx of emergency patients. Kayvanfar et al. (2025) proposed a unified framework for operating room management that integrates capacity planning and equitable surgery scheduling while mitigating surgeon-related disruption risks. It employs Markovian queueing models for OR capacity optimization and a goal programming-based scheduling model with a decomposition heuristic for equitable patient allocation. A real-world case study validates the model's effectiveness in reducing surgery cancellations and improving overall system efficiency.

2.3. Research gap

Given the pivotal role of surgery departments within hospital settings, OR planning and scheduling have remained an enduring focal point of scholarly exploration. However, a comprehensive review of the existing literature highlights several discernible gaps and unexplored dimensions in the realm of ORS problems, particularly those grappling with interval uncertainty surrounding surgery durations.

While stochastic programming and chance-constrained methods have been widely used to handle uncertainty in surgical durations (e.g. Jebali & Diabat, 2017; Azab et al., 2025; Khaniyev et al., 2020), these approaches often rely on precise knowledge of underlying probability distributions. In practice, such distributions are rarely known or are highly context-dependent, leading to limited applicability in real-world settings. Moreover, chance-constrained models, though probabilistically robust, can be computationally intensive and may not account adequately for worst-case scenarios critical in surgical environments. In contrast, the use of robust optimisation under interval uncertainty, as employed in this study, offers a distribution-free alternative that ensures solution feasibility across a defined uncertainty set. This approach is more conservative but better aligned with the uncertain, high-stakes nature of real-world OR scheduling, where missing probabilistic data is common (Fallahpour et al., 2024).

As mentioned, one notable gap lies in the absence of robust approaches, which are convenient to use, that simultaneously use just optimistic and pessimistic scenarios, which are the bounds of uncertain durations, in the context of OR scheduling. In the developed robust modelling technique of this research, only the bounds of the uncertain parameters are needed, and the uncertainty would be handled through constraints related to the best and worst scenarios. A cursory survey of the relevant literature reveals that a majority of prior research endeavours have not delved into the development of such robust methodologies. Another dimension that warrants attention is the consideration of surgeries necessitating the involvement of multiple surgeons with diverse specialties. This aspect, regrettably, has received relatively limited scholarly scrutiny but is addressed comprehensively in the present study. Furthermore, while a few studies have acknowledged the importance of factoring in the priority levels of patients, none have leveraged these levels in the daily sequencing of surgeries. In this research, a deliberate effort is made to prioritise the scheduling of vital patients within the initial sequences of the ORs each day, thereby mitigating the risk of cancellations, particularly for high-priority, emergency patients. Additionally, it is noteworthy that most prior studies have primarily focused on due dates for surgeries, often overlooking the medical necessity of allowing some surgeries to be deferred within certain time windows. In this article, the concept of time windows for surgery execution is thoughtfully incorporated to align with clinical realities.

In summation, a notable observation is the absence of a comprehensive framework in the existing literature that adeptly addresses these aforementioned gaps. Table 1 presents a comparative overview of this study in relation to other related research endeavours, underscoring the distinctiveness and comprehensiveness of our approach.

3. Methodology

In this section, we delve into the research methodology, commencing with an elucidation of the proposed optimisation model. Following this, we provide an in-depth exploration of the solution approach. To offer a concise visual representation of our methodology, we present a schematic overview in Figure 1.

3.1. Mathematical modelling

This study introduces an innovative robust approach to ORS. The central objective of the developed model is to maximise the number of successfully operated patients, with particular emphasis on their priority levels. The strategy implemented involves prioritising vital patients for surgery during the initial sequences of each day. However, it is important to note that the uncertainty surrounding surgery durations adds complexity to the scheduling process.

To address the uncertainty in surgery durations, this study applies a robust optimisation framework with interval uncertainty. This approach assumes that the uncertain parameters lie within known upper and lower bounds, avoiding the need for explicit distributional assumptions. Compared to stochastic or chance-constrained models, this method offers a more practical and reliable framework when historical data are sparse or inconsistent, a common issue in surgical planning environments. The robust approach adopted in this research is geared toward optimising the allocation of operating rooms to ensure that the cumulative duration of surgeries within each OR remains within specified limits.

Specifically, the goal is to ensure that the total time allotted to surgeries, taking into account both optimistic and pessimistic scenarios, does not exceed the predefined standard working hours for an OR. This approach serves to minimise patient cancellations and reduce patient waiting times. Furthermore, it enables the prioritised scheduling of vital patients, ensuring that they receive prompt medical attention with minimal waiting periods.

3.1.1. Assumptions

The underlying assumptions that underpin the proposed model are delineated as follows:

- The ORS strategy is open, which offers flexibility, allowing any available time to be used, while block scheduling assigns specific times or blocks to particular groups or surgeons.
- Elective patients are considered to be scheduled in the developed framework.
- The planning horizon for the scheduling framework spans two weeks (14 days).
- Each day within the ORs operates within the confines of both standard working hours and maximum allowable working hours.
- The duration of surgical procedures is inherently uncertain, with clear boundaries encompassing both optimistic and pessimistic scenarios.
- The pre- and post-activities of the surgeries are considered in the duration of the surgeries.
- Surgeons are categorised based on their respective specialties, an essential consideration in the scheduling process.
- At the commencement of the weekly planning horizon, some ORs may be pre-occupied. Since there is no time instant in the modelling approach, a sequence needs to be allocated to the pre-occupied ORs.
- The parameters associated with surgery durations are characterised by uncertainty and represented as interval parameters.
- Some surgical procedures may necessitate the involvement of more than one surgeon, reflecting the intricacies of multidisciplinary healthcare.

Table 1. Comparison of ORS studies under non-stochastic uncertainty.

Paper	Components of Scheduling	Surgery with multiple surgeons	Priority of patients in sequencing	Time window	Uncertain parameter	Type of uncertainty	Uncertainty facing approach	Simultaneous management of the best and worst case	Objective
Addis et al. (2016)	Patient, Block, Week			Latest time	Surgery duration	Robust	Bertsimas and Sim		Min delay and tardiness
Marques and Captivo (2017)	Surgery, Surgical service, Surgeon, Day, Block, Shift		✓	Latest time	Surgery duration	Robust	Bertsimas and Sim		Max equity and resource utilisation, Min waiting time
Neyshabouri and Berg (2017)	Patient, Block, Specialty				Surgery duration and length of stay	Robust	Two-stage robust		Min cost
Vali-Siar et al. (2018)	Units, Surgeon Patients, OR, Day, Time slot, Equipment			Latest time	Surgery and recovery duration	Robust	Bertsimas and Sim		Min tardiness, overtime, and idle time
Wang et al. (2019)	Surgery, OR				Surgery duration	Ambiguous distributions	Distributionally robust		Min cost
Breuer et al. (2020)	Surgeon, Other staff, Specialty, OR, Day, Block			Latest time	Surgery duration, staff availability, urgent arrival	Robust	Bertsimas and Sim		Max number of operated patients and personnel preferences
Shehadeh and Padman (2021)	Surgery, Day, Block				Surgery and ICU duration	Ambiguous distributions	Distributionally robust		Min overtime, idle time, and lack of ICU capacity
Azar et al. (2022)	Time step, patient, surgeon, OR				Surgery duration	Distributional	Chance constraints		Max number of operated patients
Dai et al. (2023)	Patient, Surgeon, OR, Date			Latest time	Surgery duration	Fuzzy	Fuzzy optimisation		Min cost
Fallahpour et al. (2024)	Units, Patient, OR, Time slot, Day		✓	Earliest and latest time	Durations, Patient arrival	Robust	Soyster		Min idle and waiting time, Max number of high-priority operated patients
This research	Patient, Surgeon, Specialty, OR, Day, Sequence	✓	✓	Earliest and latest time	Surgery duration	Robust	Novel developed robust	✓	Max number of high-priority operated patients

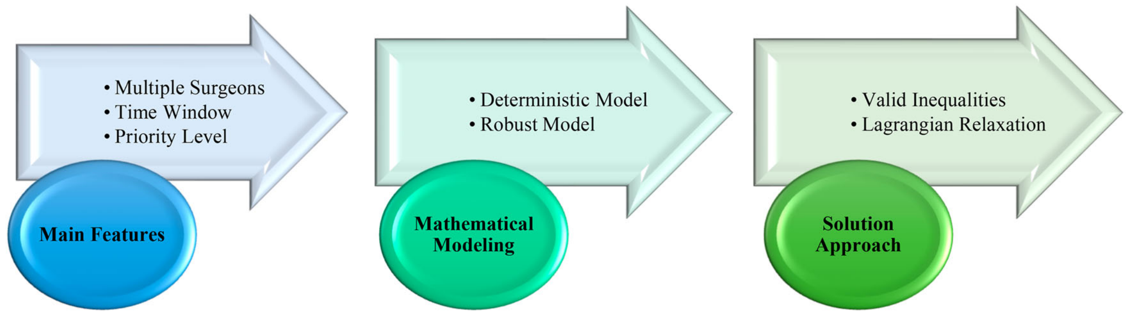

Figure 1. The procedure of the used methodology.

- It is important to note that not all surgical operations must necessarily be scheduled within the defined planning horizon.
- The model incorporates the concept of surgery priority, giving precedence to the scheduling of vital surgeries at the earliest opportunity on each day.
- Patients are not available for surgery every day, introducing an element of variability in scheduling.
- The availability of surgeons to perform surgical procedures does not occur on a daily basis, further adding to the intricacies of the model.

3.1.2. Notations

Sets.

P	Set of patients indexed by p and p'
P''	Subset of patients that make ORs pre-occupied indexed by p'', $P'' \subset P$
S	Set of surgeons indexed by s
I	Set of specialties indexed by i
S_I	Sub-set of surgeons with specialty i indexed by s_i, $S_I \subset S$
O	Set of ORs indexed by o
D	Set of days indexed by d
Q	Set of sequences of surgeries indexed by q

Parameters.

t_p	Duration of the surgery of patient p, $t_p \in [ot_p, pt_p]$
ot_p	Optimistic duration of the surgery of patient p
pt_p	Pessimistic duration of the surgery of patient p
v_p	Priority level of patient p
eo_p	The earliest day that patient p can be operated
lo_p	The latest day that patient p can be operated
m_{pi}	Binary parameter if patient p needs a surgeon with specialty i
wh	Working hours of a day
swh	Standard working hours of a day
mwh	Maximum allowed working hours of a day
pa_{pd}	Binary parameter if patient p is available on day d
sa_{sd}	Binary parameter if surgeon s is available on day d
$po_{p''odq}$	Binary parameter if OR o is pre-occupied by patient p'' on day d with sequence q

Decision variables.

y_{podq}	Binary variable if patient p has surgery in OR o on day d with sequence q
x_{ps}	Binary variable if surgeon s is the surgeon for patient p

u_{sod} Binary variable if surgeon s is assigned to OR o on day d

3.1.3. Deterministic mathematical model

$$\max z = \sum_{p,o,d,q} (v_p.(|q| - q + 1).y_{podq}) \tag{1}$$

$$\sum_{o,d,q} y_{podq} \leq 1 \forall p \tag{2}$$

$$\sum_{p} y_{podq} \leq 1 \quad \forall o, d, q \tag{3}$$

$$\sum_{p,q} y_{podq}.t_p \leq wh \quad \forall o, d \tag{4}$$

$$\sum_{s_i} x_{ps_i} \leq \sum_{o,d,q} (y_{podq}).m_{pi} \quad \forall p, i \tag{5}$$

$$\sum_{q} y_{podq} \leq \sum_{s} \left(\frac{x_{ps} + u_{sod}}{2 \sum_i m_{pi}} \right) .pa_{pd} \quad \forall p, o, d \tag{6}$$

$$\sum_{o} u_{sod} \leq sa_{sd} \quad \forall s, d \tag{7}$$

$$\sum_{o,d,q} (y_{podq}).eo_p \leq \sum_{o,d,q} (y_{podq}.|d|) \leq \sum_{o,d,q} (y_{podq}).lo_p \quad \forall p \tag{8}$$

$$y_{p''odq} \geq po_{p''odq} \quad \forall p'', o, d, q \tag{9}$$

Equation (1) constitutes the primary objective function of the novel model, which is focused on maximising the count of successfully operated patients. This optimisation objective takes into account the priority levels of the patients and endeavours to not only consider the high-priority patients in the schedule but also prioritise the scheduling of more vital patients within the initial sequences of a given day. Constraint (2) is designed to ensure that each patient is subjected to surgery at most once, preventing any redundancy in their scheduling. Constraint (3) imposes a restriction where only a single patient can undergo surgery within a specific sequence of an OR on any given day, effectively streamlining the surgical processes. Constraint (4) plays a critical role in governing the total cumulative surgery durations, ensuring that they do not surpass the designated working hours for an OR. Constraint (5) serves as a pivotal component in the allocation of surgeons to patients based on their respective specialties. This constraint is instrumental in facilitating the assignment of multiple surgeons from diverse specialties to the array of surgeries. Constraint (6) explains that a patient can be operated in an OR if his/her surgeons would be assigned to that OR. Also, this constraint considers the availability of patients. Constraint (7) places restrictions on the assignment of surgeons to ORs, permitting a surgeon to be assigned to a single OR on any given day. This constraint effectively restricts surgeons from simultaneously attending multiple ORs, enhancing the efficiency of the scheduling. Constraint (8) is closely tied to the concept of surgery time windows for each patient, contingent on whether patient p is scheduled for surgery. This constraint ensures that, if a patient is slated for surgery, the surgical procedure must occur within the predefined timeframe, extending from the earliest possible day to the latest permissible day. Constraint (9) determines the pre-occupancy of ORs.

3.1.4. Robust mathematical model

Uncertainty within the domain of ORS can significantly impact scheduling efficiency, as underscored by Varmazyar et al. (2020). This uncertainty, if not effectively managed, can manifest as idle time, overtime, and in some cases, the unfortunate cancellation of scheduled operations, as highlighted in the findings of Dodaro et al. (2019). In response to this challenge, researchers have been at the forefront of developing robust methodologies designed to navigate the uncertainties inherent in this complex scheduling domain, as exemplified in the work of Wang et al. (2023a, 2023b).

Within this specific sub-section, our focus centres on the robust ORS problem. The parameter t_p is inherently uncertain, and there is no distribution for this parameter. It is known that the duration of surgeries falls within a range delimited by ot_p and pt_p. We find it pertinent to transform Constraint (4) into a more robust formulation considering both optimistic and pessimistic surgery duration scenarios. This results in the introduction of Constraint (10) and Constraint (11), which can be characterised as robust constraints, designed to bolster the resilience of the scheduling framework in the face of uncertainty.

$$\sum_{p,q} y_{podq}.ot_p \leq swh \qquad \forall o, d \tag{10}$$

$$\sum_{p,q} y_{podq}.pt_p \leq mwh \qquad \forall o, d \tag{11}$$

Constraint (10) plays a pivotal role in maintaining the alignment of the scheduling framework with the standard working hours. It effectively governs that the cumulative duration of surgeries under optimistic scenarios within a given OR on a given day should not exceed the established standard working hours. Similarly, Constraint (11) parallels the principles upheld by Constraint (10), but it takes into account the pessimistic scenarios and the prescribed maximum working hours for the day. This constraint serves as a safeguard, ensuring that the total duration of surgeries under pessimistic assumptions within the same OR and day remains within the stipulated maximum working hours.

The robust modelling methodology employed in this investigation draws inspiration from the work of Ben-Tal and Nemirovski (1999). In our adapted approach, emphasis is placed on evaluating the upper and lower bounds of uncertain parameters, akin to assigning a value of 1 to the uncertainty level as stipulated by Ben-Tal and Nemirovski (1999). The resultant solution derived from the robust model aligns with the robust solution obtained from the deterministic model. Furthermore, the solution of the robust model always satisfies the constraints for all scenarios of uncertain parameters. It is imperative to note that the innovative robust modelling approach introduced in this study is specifically applicable to scheduling and sequencing problems characterised by uncertain duration parameters.

3.2. Solution approach

In this section, we delve into the utilisation of valid inequalities (VIs) as a potent tool for resolving the complexities inherent in the proposed model. The management of large-scale scheduling problems, characterised by intricate intricacies, often leads to extended computational times. A fundamental issue that amplifies the complexity of such problems, akin to the one developed in this study, is the abundance of potential solutions within the feasible space. To ameliorate this challenge, valid inequalities come into play as essential accelerators, serving to heighten the efficiency of computational time. In essence, these valid inequalities function as a means to constrict the solution space of the problem, as expounded by Kayvanfar et al. (2018).

In the ensuing discussion, we bring forth two specific valid inequalities designed to enhance the efficacy of the proposed model and curtail computational time. These strategic inclusions are poised to bolster the overall efficiency of the solution process.

$$\sum_{p} x_{ps} \leq \sum_{d,o} (u_{sod}).|p| \qquad \forall s \tag{12}$$

$$\sum_{p} y_{podq} \leq \sum_{p} y_{podq'} \qquad \forall o, d, q > 1, q' = q - 1 \tag{13}$$

Inequality (12) underscores the necessity that a surgeon designated to perform surgeries on patients must be assigned to an OR at least once. This condition ensures that surgeons are effectively utilised in the scheduling process. Inequality (13) serves as a critical preventative measure against unauthorised sequencing. It mandates that a sequence can attain a value only if its predecessor in the sequence possesses a value, thereby preserving the integrity and logical flow of scheduling.

Moreover, the utilisation of Lagrangian Relaxation emerges as a powerful tool to address and alleviate the robust constraints embodied in Constraints (10) and (11). Lagrangian relaxation is an approach geared towards establishing upper bounds in maximisation problems or lower bounds in minimisation problems. It has the potential to yield exact and optimal solutions, as elucidated by Lemaréchal (2001).

$$\max z = \sum_{p,o,d,q} (v_p.(|q| - q + 1).y_{podq}) - \sum_{o,d} \left(\alpha_{o,d}. \left(\sum_{p,q} (y_{podq}.ot_p) - swh \right) \right) - \sum_{o,d} \left(\beta_{o,d}. \left(\sum_{p,q} (y_{podq}.pt_p) - mwh \right) \right) \tag{14}$$

In scenarios where Lagrangian Relaxation is implemented and Constraints (10) and (11) are removed, the newly formulated objective function, incorporating Lagrangian penalties, follows the structure shown in Equation (14). In the new objective function, $\alpha_{o,d}$ and $\beta_{o,d}$ are the penalty coefficients of violating from the eliminated constraints. In the following, this version of the robust model with Lagrangian relaxation and VIs will be called the RLV model.

It is important to highlight that the employment of Lagrangian relaxation in solving the original problem, which is the robust model in this particular study, may result in a solution that is infeasible for the original problem. In this investigation, the relaxation technique is utilised as a strategic approach to achieve a comparatively good solution within a more practical timeframe.

3.3. An extension on the RLV

As highlighted in the solution approach, it becomes evident that the inclusion of Lagrangian relaxation within the objective function can yield results that may not align with the intended outcomes. This discrepancy arises from the fact that operating within the confines of the standard and maximum allowed working hours can artificially enhance the objective function. However, this unintended consequence may inadvertently lead to the scheduling of fewer patients, which is inherently at odds with the primary objective.

In response to this concern, this sub-section introduces a novel model that addresses this challenge by relocating the Lagrangian penalties from the objective function and situating them within distinct constraints on the left-hand side. Within this revised model, we introduce two positive variables denoted as SE_{od} and ME_{od}, which pertain to any potential excesses beyond the stipulated working hours. These variables are thoughtfully incorporated into the right-hand side of the constraints and are also integrated into the objective function, where they are multiplied by their respective penalty coefficients. The outcome of this transformation manifests in a new objective function and revised constraints, encapsulated in Relations (15) through (17):

$$\max z = \sum_{p,o,d,q} (v_p.(|q| - q + 1).y_{podq}) - \sum_{o,d} (\alpha_{o,d}.SE_{od}) - \sum_{o,d} (\beta_{o,d}.ME_{od}) \tag{15}$$

$$\sum_{p,q} (y_{podq}.ot_p) - swh \le SE_{od} \qquad \forall o, d \tag{16}$$

$$\sum_{p,q} (y_{podq}.pt_p) - mwh \le ME_{od} \qquad \forall o, d \tag{17}$$

It is noticeable to mention that the solution of the extended RLV, with value of 0 for both penalty positive variables, is feasible in the original problem which is the robust model. It's also worth highlighting that the upcoming section will delve into a case study, specifically scrutinising the RLV model. Furthermore, the sensitivity analysis will encompass a comparative evaluation of the extended and RLV models.

4. Case study and results

This section is dedicated to the practical application of the problem presented in Section 3.2, involving a real-world case study. A dataset pertaining to a surgical department within a medical facility has been made

Table 2. The value of input parameters.

Number of patients	Time period (days)	Number of ORs	Number of surgeons	Number of specialties
100	14	2	10	4
Standard working hours		Maximum allowed working hours		Penalty coefficients
8		12		0.01

Table 3. Assignment of surgeons to ORs.

		D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12	D13	D14
S1	OR2		1			1		1							1
S2	OR1		1												
S2	OR2	1			1	1			1			1		1	
S3	OR2						1							1	1
S4	OR1	1													
S4	OR2				1			1							
S5	OR1			1	1	1				1					
S5	OR2		1				1		1			1			
S6	OR1			1											
S6	OR2						1	1	1				1		1
S7	OR1				1		1	1		1		1			
S7	OR2								1		1			1	1
S8	OR1		1			1	1		1		1	1			1
S8	OR2													1	
S9	OR1	1	1	1		1	1	1			1		1	1	
S10	OR1					1	1	1	1			1	1	1	1

available, encompassing essential information about patients, their specific surgical requirements, the specialties of the surgeons needed, as well as the quantities of both ORs and surgeons. Additionally, a range has been established for the anticipated duration of each surgical procedure. This dataset serves as the basis for the application of the proposed ORS model.

Table 2 succinctly showcases the principal input parameters central to the problem, providing an overview of the core data elements. Patients have been systematically categorised into three distinct groups, primarily predicated upon their priority levels. Vital patients are assigned a priority level of 3, while patients classified as low-risk and those without risk are allocated priority levels of 2 and 1, respectively. Furthermore, each patient's surgical schedule adheres to a predetermined time window, such that if a patient is scheduled for surgery, the procedure's date must fall within the defined boundaries, extending from the earliest plausible day to the latest admissible day.

The case study was executed on a computing system equipped with an AMD A8-7410 APU, complemented by AMD Radeon R5 Graphics, operating at a clock speed of 2.20 GHz and boasting 16 GB of RAM. To address the binary programming, the widely recognised commercial software GAMS 25.1.2 was employed in conjunction with the CPLEX solver. The computational process required approximately 18 min to reach completion. Upon the successful resolution of the robust problem, the resulting value of the objective function was determined to be 579.18, accompanied by a minimal gap of 2 percent. Additionally, the outcome of the assignment of surgeons to the respective ORs is encapsulated within Table 3 for reference and analysis.

A total of 91 patients have been designated for surgical procedures to be conducted over a span of 14 days, a numerical derivation provided by Equation (18).

$$\text{Number of operated patient} = \sum_{p,o,d,q} y_{podq} \tag{18}$$

Within this context, an illustrative depiction of the surgical schedule for OR1 on the second day has been visually represented in Figure 2. It is notable that this visualisation encompasses both the pessimistic and optimistic scenarios for surgery durations. Figure 2 conveys that the cumulative time associated with the optimistic estimates for surgery durations remains within the 8-hour threshold. Conversely, when the pessimistic durations are considered, the accumulated time extends beyond the 12-hour mark, an outcome stemming from the relaxation process. In essence, relaxing the robust constraints implies that the problem is approached with a more lenient, permissive robust strategy. However, it is important to note that by forgoing this relaxation and opting for a more rigorous computational approach, the ORs would adhere strictly to the 8-hour

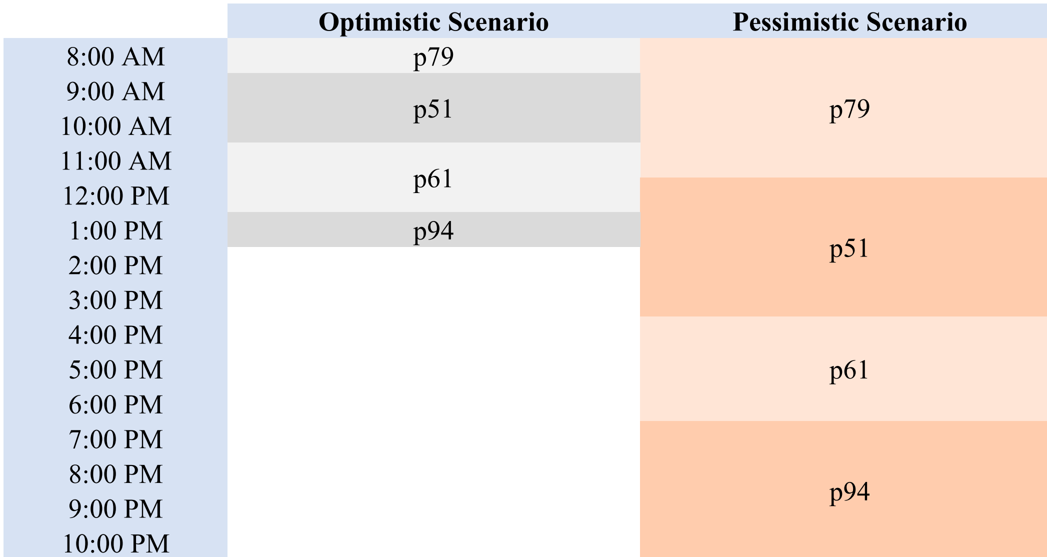

Figure 2. Schedule of OR1 on day 2.

and 12-hour limits for optimistic and pessimistic surgery durations, respectively. This, of course, comes at the cost of increased computation time. Subsequently, the ensuing section will delve into the results arising from the application of the model, detailed in Section 3.2, within the framework of the aforementioned case study, herein referred to as the 'base case'.

5. Sensitivity analysis and managerial insights

Within this section, a comprehensive exploration of the sensitivity analysis is conducted, complemented by the corresponding managerial insights. The assessment encompasses an array of influential factors, including the availability of patients and surgeons, the priority levels of patients, working-hour dynamics, an examination of the penalty coefficients associated with Lagrangian relaxation, and time efficiency comparison. This systematic evaluation aims to provide a robust understanding of how various parameters impact the operational aspects and decision-making processes pertinent to the study's focus.

5.1. Availability of patients and surgeons

In this particular sub-section, we approach the problem by positing an ideal scenario where all patients and surgeons are assumed to be available every day. The resulting objective value, in this context, is determined to be 639.78. A notable contrast emerges when we compare this objective value with that of the base case, which stood at 579.18. This shows a 10.46% improvement in the objective value. This observation underscores a pivotal insight: the greater the availability of patients and surgeons, the more favourable the Operating Room Scheduling (ORS) outcome becomes.

The increase in the objective function is inherently tied to the number of patients who can be accommodated within the schedule. In this scenario, all 100 patients can be successfully scheduled for surgery, a testament to the substantial enhancement in operational efficiency achieved when patients and surgeons are readily accessible on all days. Availability of patients and surgeons means a 9.89% increase in the number of operated patients (Figure 3).

5.2. Priority level

In this research, we have introduced the priority level of patients as a crucial factor within the objective function of our model, with the aim of prioritising the treatment of patients in critical conditions during the

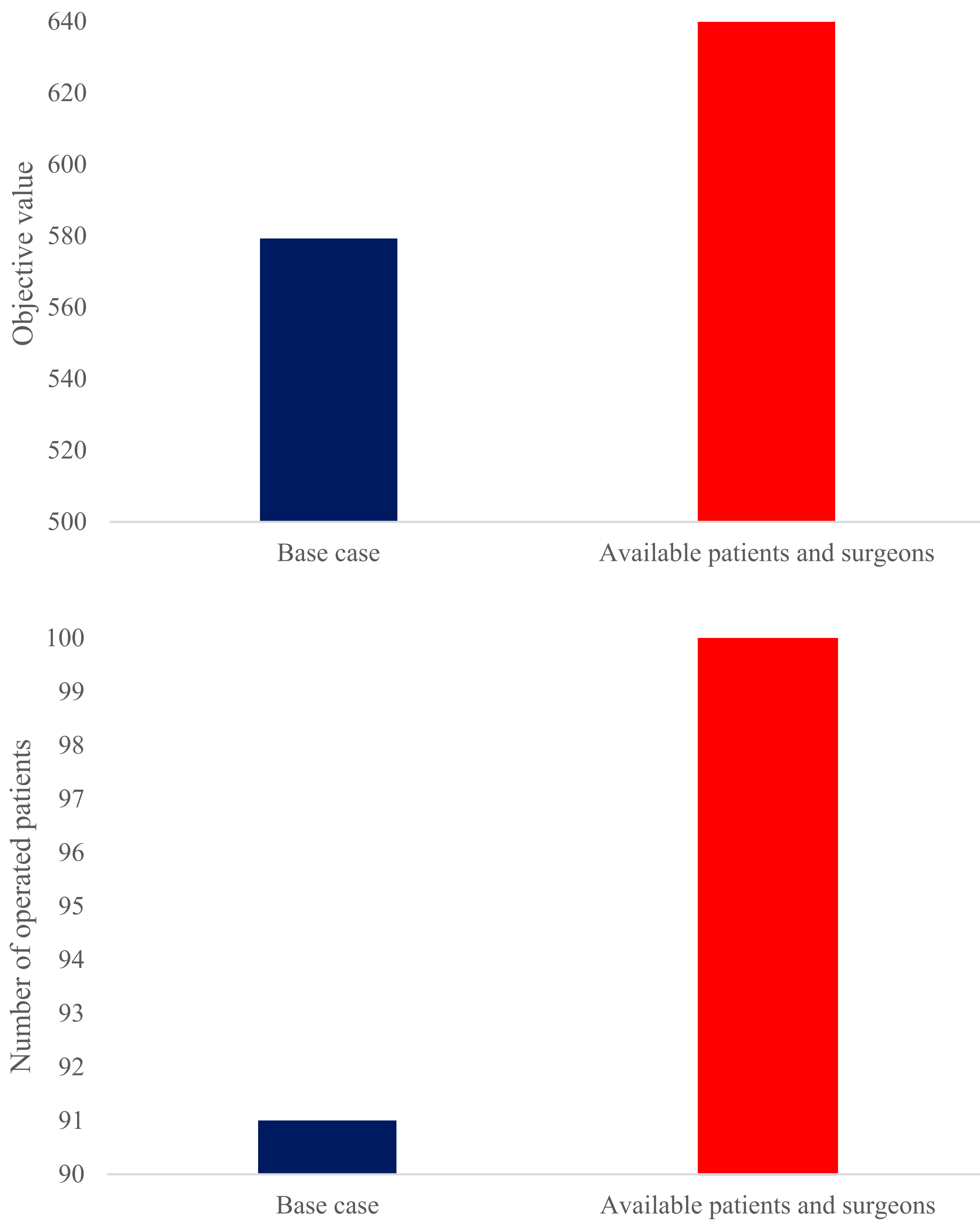

Figure 3. Sensitivity analysis on the availability of patients and surgeons.

initial scheduling sequences. This subsection is devoted to an exploration of the repercussions associated with omitting the consideration of priority levels within the objective function.

To disregard the priority level of patients in our analysis, we must reformulate the objective function according to Equation (19). This adjustment allows us to discern the impact of excluding the priority aspect from our decision-making process and to comprehensively evaluate the consequences of this omission on the overall scheduling dynamics.

$$\max z = \sum_{p,o,d,q} (y_{podq}) - \sum_{o,d} \alpha_{o,d}.\left(\sum_{p,q} (y_{podq}.ot_p) - swh\right) - \sum_{o,d} \beta_{o,d}.\left(\sum_{p,q} (y_{podq}.pt_p) - mwh\right) \quad (19)$$

In this particular instance, the objective function yields a value of 94.1. Moreover, the number of patients who have undergone surgery amounts to 93, marking an increase of 2 patients compared to the base case.

This surge in the number of operated patients can be ascribed to the inherent characteristics of the objective function. In the base case, the prioritisation of scheduling vital patients during the initial sequences is a pivotal factor that contributes to the enhancement of the objective value. Conversely, in this scenario, the overarching optimisation objective revolves around maximising the number of patients operated upon. The core distinction lies in the emphasis between the two cases: one leans towards prioritising vital patients, while the other leans towards the overall optimisation of patient treatment, irrespective of their priority level.

In addition, to demonstrate the effects of the priority level from a different insight, we solved the model in another scenario with the following objective function, as Equation (20):

$$\max z = \sum_{p,o,d,q} (v_p.y_{podq}) - \sum_{o,d} (\alpha_{o,d}.SE_{od}) - \sum_{o,d} (\beta_{o,d}.ME_{od}) \tag{20}$$

Which is similar to Fallahpour et al. (2024). The average surgery sequence for high-priority operated patients in this case (2.7) has a greater value than the primary problem (2.2). It means that patients with higher priorities are being operated on in the first sequences of each day which are at a lower risk of cancellation. This shows the effectiveness of the proposed equation for considering priorities in the sequencing of the surgeries.

5.3. Working hours and relaxation

Figure 4 presents the solution to the problem without employing relaxation techniques; instead, robust constraints are employed to assess the influence of the surgery department's working hours on the quantity of patients who undergo surgery. The visual representation of the data illustrates a clear correlation: as working hours within the surgery department increase, so does the number of patients receive surgical treatment. It is essential to highlight that a similar trend can be observed when employing relaxed robust constraints, provided that the penalty coefficients are sufficiently substantial. This insight underscores the pivotal role that working hours play in optimising patient throughput within the context of surgery scheduling. In this chart, [9, 13] means that 9 and 13 h are considered for the standard and maximum allowed working hours, respectively.

5.4. Penalty coefficient

In this section, a sensitivity analysis focuses on the impact of varying penalty coefficients associated with Lagrangian relaxation, as visualised in Figure 5. The graphical representation in Figure 5 provides a valuable insight: augmenting the penalty coefficients has the effect of enhancing the overall objective function value.

However, it is noteworthy that this improvement in the objective value is coupled with a reduction in the number of patients who can undergo surgery. To illustrate, when employing penalty coefficients set at a value of 0.5, the number of patients receiving treatment dwindles to a mere 67. This outcome can be attributed to the inclusion of the penalty term within the objective function. Essentially, the pursuit of operating patients within sequence 4 is compromised when the penalty coefficients are increased, as the optimisation objective shifts towards adhering to standard and maximum working hours, prioritising efficiency over sequence 4 patient operations, which is a notable but not necessarily logical outcome.

5.5. Comparative analysis of the extended model

In this section, we conduct a comparative analysis between the results obtained from the extended model and the RLV model. The extended model is executed under identical conditions as the base case. In this scenario, the objective function yields a value of 578, with a minor 3 percent gap. Furthermore, the number of patients undergoing surgery stands at 91, mirroring the outcome of the base case. Figure 6 provides a visual representation of the number of patients who receive treatment in both the extended and RLV models, as influenced by varying penalty coefficient values. Remarkably, Figure 6 illustrates that the number of patients who undergo surgery, and consequently the objective function, remain largely unaffected by fluctuations in the penalty coefficients. This indicates robustness and consistency in the performance of the models across a

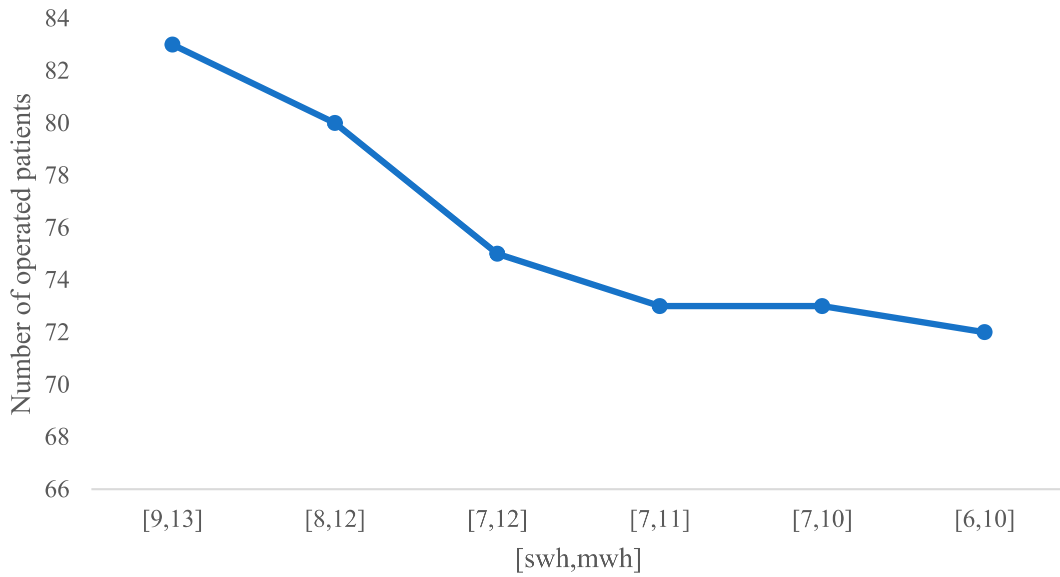

Figure 4. Sensitivity analysis on working hours.

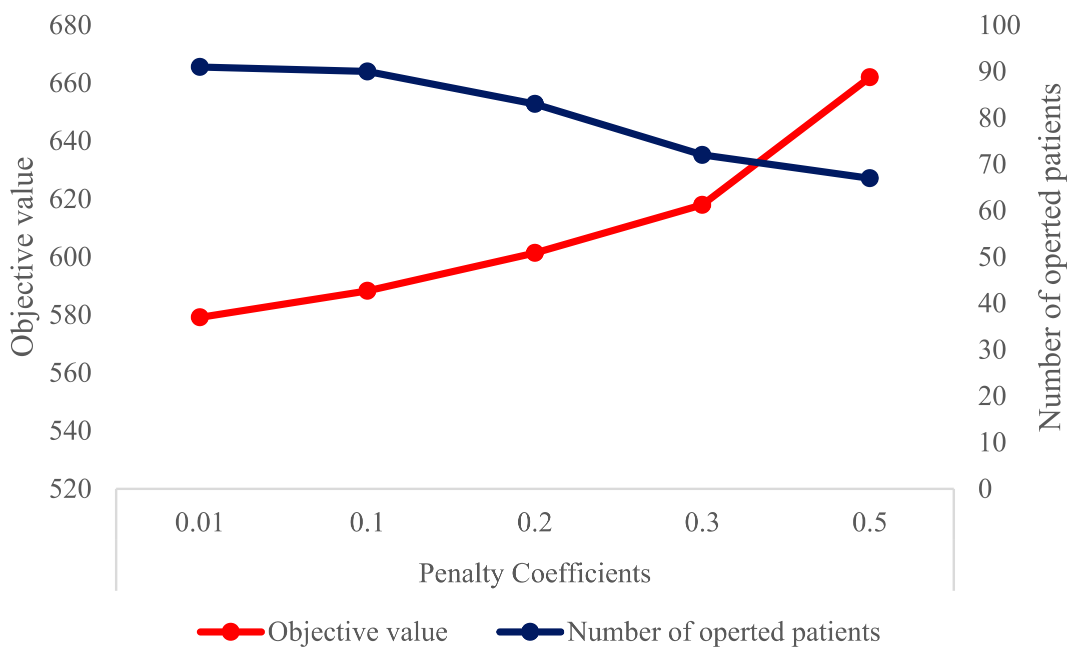

Figure 5. Sensitivity analysis on the penalty coefficients of Lagrangian relaxation.

range of penalty coefficient values. In conclusion, the extended model reduces the objective sensitivity on fine-tuning of penalty coefficients, which is desirable from a management point of view. According to this chart, in the extended model, not only the need for tuning the penalty coefficients is reduced, but also the number of operated patients reaches its highest possible number, which is desired in the context of OR management.

5.6. Time efficiency comparison

The computation time of the three models across different scales of the problem is plotted in Figure 7. All instances are executed in the GAMS software. It's important to highlight that the instance scale ($|P|.|S|.|I|.|O|.|D|.|Q|$) was manipulated by varying the size of sets in the ORS model. To illustrate, in the initial instance, there were 10 patients, 4 surgeons, 2 specialties, 2 ORs, 2 days, and 4 sequences. Figure 7

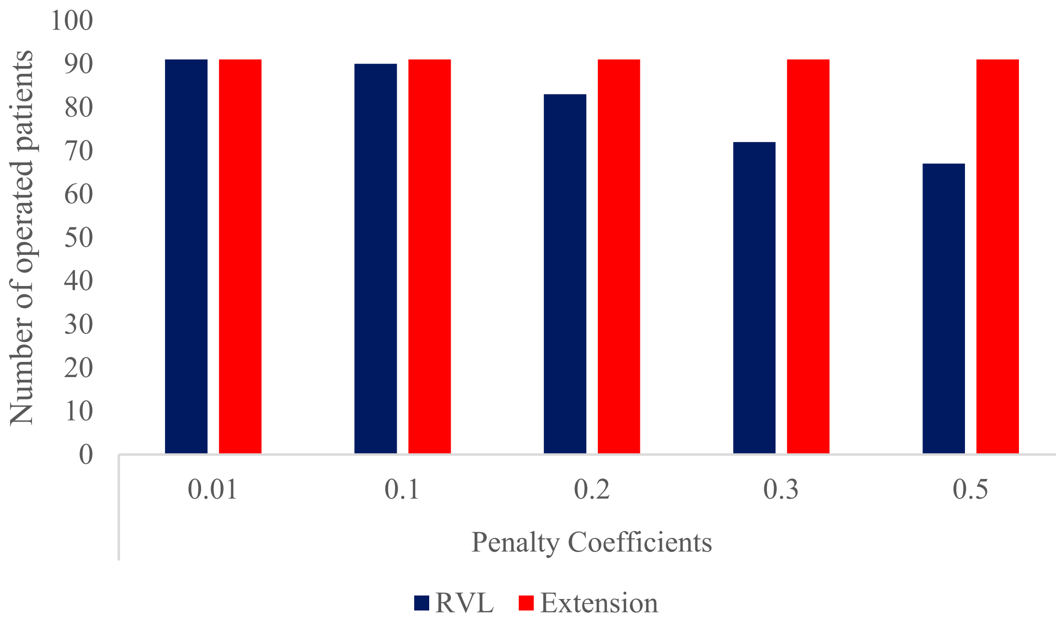

Figure 6. Comparison of the extended and RLV model based on changing penalty coefficients.

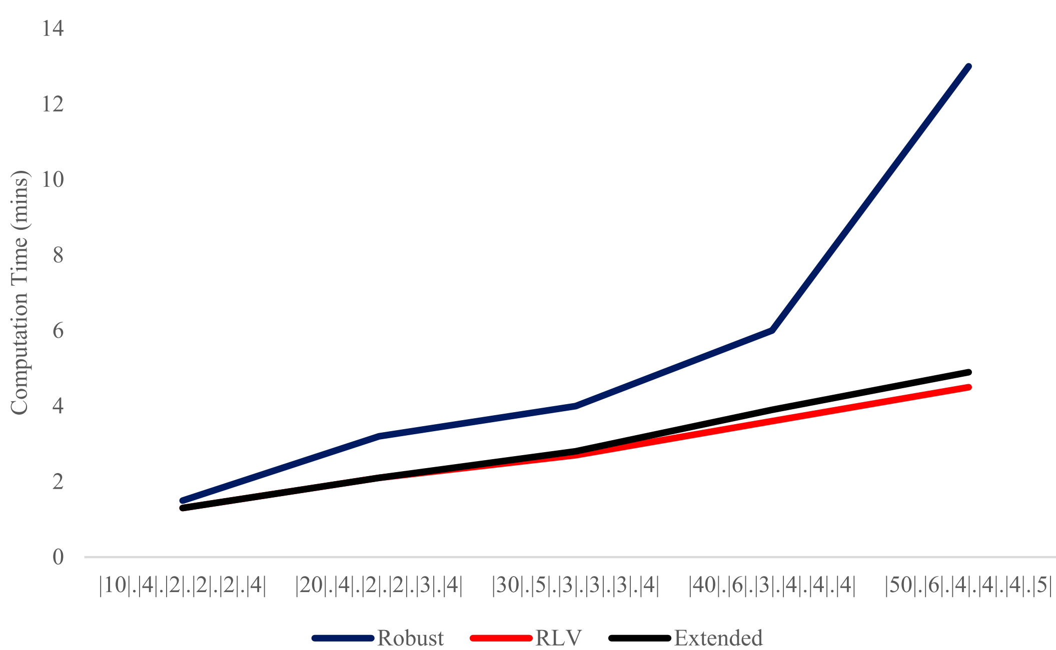

Figure 7. Time efficiency comparison.

shows that the execution time on small scales is nearly the same. As the scale of the problem becomes larger, the time efficiency of the RLV and extended model becomes more significant.

As illustrated in Figure 7, while all three models (Robust, RLV, and Extended) demonstrate comparable performance on small-scale instances, the difference in computational efficiency becomes increasingly evident as the problem size grows. Specifically, the Robust model exhibits significantly higher computation times in larger instances, over 13 min, due to its structural complexity and large number of constraints. In contrast, both the RLV and Extended models demonstrate superior scalability and reduced computational burden.

However, it is important to note that the RLV model, due to its reliance on Lagrangian relaxation, may occasionally produce infeasible solutions, particularly when penalty coefficients are not tuned properly. To address this issue, we developed the Extended model, which integrates additional variables and constraints to reinforce feasibility. While the Extended model requires slightly more computational time than RLV, the trade-off is justified, as it significantly reduces the risk of infeasibility. Thus, the Extended model strikes a balance between solution robustness and computational efficiency, making it a practically advantageous option, especially for real-world large-scale scheduling applications.

5.7. Managerial and practical insights

This sub-section offers a series of practical and managerial insights, drawing upon the outcomes of the case study and the sensitivity analyses conducted.

The robust approach developed in this study is versatile and can find application in other scheduling models. Its primary strength lies in its simplicity and user-friendliness as well as its simultaneous consideration of the best and worst cases. Also, the developed solution approach and the model structure are time-efficient and make it possible to solve large-scale problems. However, an observation from the study suggests that results achieved through the model with Lagrangian relaxation may not always be feasible in the context of robust constraints. Decision-makers facing such a dilemma should opt for the robust constraints model as it guarantees compliance with working hours, minimising operational risks.

As highlighted in sub-section 5.1, healthcare managers should consider soliciting patients' preferences regarding their readiness for surgery across a specified timeframe, encompassing all available days within that period. By incorporating this approach, operating room scheduling can be optimised to accommodate more surgeries, thereby contributing to heightened productivity. As revealed in sub-section 5.2, balancing the conflicting objectives of increasing the number of surgeries performed while prioritising vital patients in early sequences is of paramount importance. An excessive focus on patient priority levels may raise costs and lower revenue. Utilising Pareto-based multi-objective methodologies could offer advantages in addressing this particular challenge. Section 5.2 also indicates that the structure of scheduling models can consider not only priorities for the execution of the surgeries in the planning period but also the sequence of the surgery on the specific day. Sub-section 5.3 highlights that reducing standard or maximum allowed working hours may lead to a reduced number of surgeries performed, particularly when accompanied by significant penalty coefficients or in the absence of relaxation. However, increasing working hours excessively is not a practical solution, as it can negatively impact the quality of medical services and burden the medical personnel, particularly surgeons. Sub-sections 5.4 and 5.5 underscore the critical nature of fine-tuning the penalty coefficients in the RVM model, as they substantially affect the solutions. Inadequately adjusted coefficients can lead to sub-optimal scheduling, a challenge effectively addressed by the extended model. The decision for the best value of the penalty coefficients depends on the decision maker's desires. Section 5.5 also indicates that the use of Lagrangian relaxation may prevent reaching the desired schedule while the solution is optimal. The extended model handled this issue and provided an efficient and effective version of the model structure. Section 5.6 shows that although the extended model is weaker than the RLV in terms of time efficiency, compared to the robust model, it is strongly efficient, and its weakness against RLV is justifiable. The chart presenting the computation time comparison in this section justifies the need for developing an efficient solution approach for the proposed framework.

6. Conclusion, limitations, and future directions

This study presents a novel approach to address operating room scheduling (ORS) problems for elective patients under an open scheduling strategy, making a valuable contribution to the existing body of research on the management of surgery departments. The key innovation in this research lies in its consideration of surgery durations as uncertain intervals, meaning that each surgery is associated with both a lower and an upper bound for its duration. To tackle this uncertainty, a novel robust approach has been developed. Under this approach, the total time for all surgeries must not exceed the standard working time when all surgeries are optimistically executed, and similarly, it must not surpass the maximum working time allowed when considering pessimistic scenarios.

Furthermore, the scheduling model introduced in this research takes into account the priority levels of patients, with a focus on prioritising vital patients for early scheduling. Additionally, the concept of time windows for surgery execution, encompassing the earliest and latest feasible times for each operation, is incorporated into the model. The model is designed to accommodate surgeries that involve multiple surgeons from various specialties.

To address the uncertainty inherent in surgical durations, this study introduces a robust-scenario generation mechanism that captures variability while preserving model tractability. Recognising the practical limitations of standard robust models, we proposed an extended formulation that enhances feasibility, scalability, and computational efficiency. To validate the effectiveness of this approach, it was applied to a real-world case study. The results highlight the practicality of using robust optimisation in ORS under uncertainty, demonstrating its ability to deliver reliable solutions across a range of scenarios. Unlike stochastic or chance-constrained methods, our interval-based robust approach does not rely on precise distributional assumptions, making it especially relevant in hospital environments where historical data may be sparse or non-stationary. These contributions position our model as both conceptually distinctive and practically applicable for large-scale, real-world healthcare scheduling challenges.

This study encountered several notable limitations during its execution. One primary challenge was the acquisition of a suitable dataset to apply the proposed model effectively. Gathering comprehensive and relevant data for the study posed a significant hurdle. Moreover, the complexity of the model itself and the extensive scope of the case study added to the overall challenge. However, to address these complexities, a well-suited solution approach was employed.

The findings of this research shed light on several key takeaways. Firstly, the study demonstrates that the uncertainty associated with surgery durations can be successfully managed through the methodology presented. Additionally, by prioritising the scheduling of vital patients during the initial sequences of a day, the rate of cancellations for these high-priority operations can be minimised, ultimately reducing potential health risks to these patients. Furthermore, this research successfully addresses the existing gap in the modelling of an ORS system that takes into account surgeries requiring multiple surgeons from diverse specialties, adding depth and comprehensiveness to this field of study.

As we conclude this research, several promising avenues for future exploration and inquiry present themselves. These directions are pivotal for extending the understanding of the field studied and improving practical applications. The following suggestions delineate these research trajectories:

– Meta-Heuristics for Large-Scale Instances: The utilisation of meta-heuristic techniques holds great promise, particularly in addressing the complexities inherent in large-scale instances of the proposed model. Developing and implementing a suitable meta-heuristic method stands as an essential initial step in this direction. Prior research, as exemplified by Toub et al. (2022), underscores the significance of this approach.

– Incorporating Additional Uncertainties: While this study primarily focused on managing uncertainty related to surgery durations, future research should expand its scope to encompass other sources of uncertainty. This could entail the integration of variables such as emergency patient arrivals (J.-J. Wang et al., 2023a) and disruptions stemming from equipment and surgeon-related issues (Kamran et al., 2020).

– Integration of Surgery Blocks: The inclusion of surgery blocks within the proposed model is another promising avenue for exploration. This direction, as demonstrated in the work of Norouzi et al. (2022), can contribute valuable insights into optimising the scheduling of surgery blocks within the broader context of operating room management.

– Integrated Approach for Downstream Units: Future research endeavours may delve into the scheduling of downstream units in a more integrated manner. The study by Kayvanfar et al. (2021) illustrates the significance of adopting a holistic approach that considers the interdependencies and interactions between various units within a healthcare facility.

– Machine Learning for Patient Categorisation: Embracing machine learning algorithms to categorise patients based on their specific medical conditions and priority levels prior to scheduling is a compelling avenue. This approach, as suggested by Rahiminia et al. (2025), presents an innovative means of enhancing the precision and adaptability of the scheduling process, aligning it with the unique needs and conditions of each patient.

These prospective research directions collectively represent opportunities to further enrich the field of operating room scheduling and management, ultimately advancing the efficiency, quality, and patient-centric nature of healthcare delivery. Researchers and scholars are encouraged to explore these areas to contribute to the ongoing evolution of this critical domain.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

Data availability statement

The authors confirm that the acquiring scheme of data supporting the findings of this study is available based on request.

AI-assisted technologies

The current study uses the ChatGPT AI tool for passage checking and grammatical revision. We guarantee the validity of the passing, and human knowledge verifies its accuracy.

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