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Group Arrivals of Emergency Patients: A Resilient Approach to Operating Room Scheduling

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ABSTRACT

Addressing the challenge of operating-room management under unpredictable group arrivals of emergency patients, we propose a resilient, block-based scheduling strategy that balances elective throughput with rapid emergency response. The day is partitioned into contiguous time blocks; an initial elective surgery schedule is generated for the full horizon and then dynamically updated at the start of each block as emergency arrivals materialize. Our policy preferentially assigns shorter elective procedures to blocks with a higher estimated probability of emergency arrivals, thereby reducing elective disruption, increasing the likelihood of on-time completion for scheduled cases, and expediting care for emergency patients. To support this operational design, we formulated an initial mixed-integer programming model for baseline planning, and two rescheduling models that are triggered when emergencies occur. For computational tractability on realistic instance sizes, we solved these models using the Invasive Weed Optimization (IWO) metaheuristic. Computational experiments on large, randomly generated benchmarks indicate that IWO consistently produces high-quality solutions within modest computation times, preserving elective performance while significantly improving system resilience to grouped emergency arrivals. The proposed framework is readily adaptable to hospital preferences and uncertainty estimates, making it suitable for practical deployment.

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1) Introduction

Hospitals, as a fundamental component of the healthcare system, encompass various specialized departments, including operating rooms (ORs), recovery rooms, and special care units. Surgical procedures constitute a significant portion, accounting for approximately 60% of patients seeking hospitalization, contributing to approximately 40% of the overall hospital expenditure (Guerriero & Guido, 2011; van Essen et al., 2012). Therefore, the ORs represent a bottleneck in cost and income optimization (Aringhieri et al., 2015).

The organization of ORs within the medical field involves allocating specific functions to various specialties or departments, each of which is dedicated to a specific patient group or set of diseases. A daily scheduling procedure is required to effectively manage the surgical procedures within these specialties. This procedure aims to coordinate and arrange surgeries within the ORs. Typically, a preliminary scheduling for elective patients is established one day before the scheduled surgery day. This serves as a baseline for planning upcoming elective surgeries. However, a significant challenge arises when emergency cases occur on the actual surgery day, as they cannot be accommodated within the initial scheduling. Each of these emergency patients has a waiting time limit that is determined according to the severity of the disease (Miao & Wang, 2021). According to studies conducted by McIsaac et al. (2017), Smith et al. (2013), and Litvak (2010), the standard waiting time for each patient, as considered in many hospitals, is classified into five classes. Therefore, every emergency patient should enter the OR before the waiting time is over.

Previous studies have predominantly focused on individual emergency patient arrivals, overlooking the potential impact of group arrivals of emergency patients (e.g., Eshghali et al., 2024; Miao & Wang, 2021). This narrow approach may fail to account for important aspects of the complex emergency arrival process, which could be crucial for effective OR scheduling and optimization. Healthcare facilities should acknowledge the possibility of single or group emergency patient entries at any given moment and prioritize preparedness in implementing suitable response measures to ensure prompt and appropriate care for patients in urgent medical need. When unexpected events lead to a surge in emergency cases, there is a possibility of citizens sustaining injuries and requiring immediate medical attention, resulting in an increased demand for hospital services and emergency surgical procedures. This influx of unplanned emergency arrivals has the potential to disrupt the typical scheduling and utilization of operating rooms. The existing literature has not adequately addressed the challenge of managing group-level emergency patient arrivals. In the face of a surge of unplanned emergency cases requiring immediate surgical intervention, ORs must contend with the disruption caused by this influx of group-level arrivals. If the waiting time for all or some of these emergency patients exceeds the available operating room capacity, with no empty rooms or insufficient room availability, it can lead to a scheduling disaster, failing the operating room management plan.

However, it is important to note that such group arrivals of emergency patients do not always occur. Therefore, effective OR scheduling approaches must be flexible enough to accommodate various scenarios, including days with no emergency patient arrivals, single emergency patient arrivals, and group arrivals of emergency patients. Furthermore, these scheduling strategies should align with the overarching goals and priorities of OR managers. By developing comprehensive and adaptable scheduling frameworks, hospitals can better prepare for and respond to the unpredictable nature of emergency patient arrivals, ensuring the continued efficiency and effectiveness of their surgical services.

The contributions of this paper are summarized as follows:

- The fully integrated model is developed for the ORs. The proposed model is integrated into three concepts:

1. Considering elective patients and emergency patients
2. Addressing both individual and group arrivals of emergency patients
3. Proposing daily initial scheduling, and rescheduling mathematical models

- Using allocation and prioritization to accept emergency arrivals faster
- Dividing the total working time into several time blocks for better management of group arrivals of emergency patients so that rescheduling is needed at the beginning of each time block.
- Concerning the problem structure, an efficient invasive weed optimization (IWO) is presented to solve large instances

The remainder of this paper is organized as follows: Section 2 provides a comprehensive literature review on the subject matter. Section 3 presents the problem definition, while Section 4 outlines the development of the solution method. Section 5 details the computational experiments conducted to assess the proposed method. Finally, Section 6 summarizes the conclusion of the study.

2) Literature Review

In the operational scheduling of patients, there are two primary categories elective and non-elective, with the latter typically considered emergency (Cardoen et al., 2009). The operational scheduling process encompasses two distinct phases: offline and online (Cardoen et al., 2010). An allocation scheduling is meticulously prepared during the offline or initial scheduling phase. This involves determining the allocation of elective patients to operating rooms, surgeons, and other resources (Kamran et al., 2020). This scheduling must be finalized before the day of the surgery, as the number of elective patients and their availability is known with certainty. However, the number and time of arrival of emergency or non-elective patients is not known in advance. To address this uncertainty, initial preventive scheduling is created, essentially the initial scheduling augmented with appropriate strategies to enhance the response to potential emergency arrivals. In contrast, the online scheduling or rescheduling is determined on the day of the surgery. The decisions specified in this dynamic scheduling are implemented on the day of operation. If an emergency arrival occurs on the day of the surgery, the initial scheduling is no longer valid, and it must be revised so that mitigates the adverse effects of this unforeseen event. The goal is to generate a revised scheduling that not only accommodates the emergency patient but also maintains optimal scheduling for the remainder of the day's operations (Eshghali et al., 2024; Miao & Wang, 2021).

In the study by Miao and Wang (2021), the fundamental assumption is the presence of unpredictable emergency patients, for whom the arrival time is unknown a priori. The primary objective is to devise a solution that can effectively accommodate both the scheduled, elective patients as well as these unplanned, emergency cases. The desired approach involves the strategic consideration of time buffers within the initial scheduling process. This begins with the allocation of a designated number of surgical suites, specifically reserved to manage emergency patient arrivals. Subsequently, these reserved time buffers are meticulously positioned within the initial scheduling in a manner that ensures the availability of at least one empty operating room upon the arrival of each emergency patient.

In the study by Tang and Wang (2015), the scheduling process is predicated solely on the consideration of the lower and upper bounds of emergency time demand. Within this framework, the researchers have developed an initial scheduling using a robust optimization model, thereby ensuring a stable foundation for the overall operational planning. This research approach centers around a preventive scheduling methodology that is informed by varying levels of emergency demand information. Particularly, the allocation of future emergency time slots is based on either partial or full knowledge of the anticipated emergency requirements. However, a key limitation of this approach is the lack of explicit consideration for emergency admissions with defined time constraints. Subsequently, several studies (Freeman et al., 2015; Latorre-Núñez et al., 2016; van Essen et al., 2012) proposed preventive scheduling techniques that leveraged the concept of break in the moment, which refers to the intervals after an elective surgery concludes and the associated operating room becomes available for potential emergency procedures. In the study by Eshghali et al. (2024), a hybrid approach that leverages machine learning and geographic information systems was proposed to predict the arrival time of emergency patients. Upon their arrival, a real-time evaluation of the operating room availability is conducted, and if an operating room is available, the emergency surgery commences. In contrast, if the operating room is occupied, the urgency of the emergency patient and the elective patient undergoing surgery is compared, and the surgery for the patient with a higher priority is initiated. If an emergency procedure is conducted, rescheduling is undertaken to accommodate the disruption in the scheduling. In the study by Miao and Wang (2021), a comprehensive analysis was conducted to assess the impact of emergency patient arrivals and rescheduling practices on the satisfaction levels of three crucial stakeholders: the operating room manager, the medical staff, and elective patients. The study aimed to balance the efficient utilization of the operating room resources with minimizing the disruption and dissatisfaction experienced by each stakeholder group, thereby maximizing overall system performance and satisfaction. Goodarzian et al. (2021) propose a bi-objective mixed-integer linear programming model for a multi-level, multi-product, and multi-period medicine supply chain network, optimizing location, production, distribution, transportation, and inventory management while incorporating a production technology policy. Tadarok et al. (2021) address the challenge of blood shortage and wastage in the blood supply chain by proposing an integer programming model to minimize costs, shortage, and wastage in a hospital setting. Considering different blood groups and real-world uncertainty, the authors employ a robust fuzzy possibilistic programming approach, demonstrating its application and conducting sensitivity analysis for validation. The model effectively manages uncertainty, achieving a significantly lower objective function value than probabilistic approaches. In the study of Fallahpour et al. (2024), the complexities of OR planning and scheduling are addressed using a Mixed Integer Programming (MIP) framework. The authors aim to optimize resource allocation and minimize patient wait times amidst uncertainties in surgical duration and patient influx. They emphasize the importance of incorporating upstream and downstream units such as the Pre-operative Holding Unit (PHU), Post Anesthesia Care Unit (PACU), and Intensive Care Unit (ICU) in OR planning. To manage uncertainties, a robust optimization strategy is employed, resulting in Pareto-optimal solutions. This study serves as a foundation for our research, highlighting the significance of efficient OR planning and the need for robust optimization techniques. Almoghrabi and Sagnol (2024) tackle the elective surgery planning problem in hospitals where operating rooms cater to both elective and emergency patients. The problem involves two phases: offline (patient selection and scheduling) and online (emergency patient insertion and cancellation management). The goal is to minimize costs related to patient assignment, cancellations, overtime, waiting time, and idle time. This study emphasizes considering all operational decisions and uncertainties, such as emergency arrivals and surgical durations when evaluating planning strategies. Miao and Wang (2023) address the challenge of distributed surgical scheduling across multiple hospitals and days, aiming to minimize total expected costs amidst uncertainties such as treatment durations and emergency demands. They develop a two-stage stochastic integer programming model for determining elective service operations and patient assignments within a hospital alliance. Y. Wang et al. (2024) present a novel data-driven model for optimizing surgery scheduling, addressing uncertainties in surgery durations and dynamic emergency patient arrivals. A rolling horizon scheme dynamically reschedules and prioritizes emergency patients upon arrival. Ebrahimy Zade and Fakhrzad (2013) examine the scheduling problem with nonresumable jobs and maintenance processes, aiming to minimize makespan under two different strategies: predetermined maintenance time and maximum job completion.

Across the literature, various studies have proposed allocation and prioritization schemes for elective patients to maximize their satisfaction (Anjomshoa et al., 2018; Bowers, 2011; Durán et al., 2017; Mahpouya et al., 2026; Marques & Captivo, 2017; Marques et al., 2012; Rachuba & Werners, 2014; Vaghfi Mohebbi et al., 2025). These methods typically employ first-in-first-out (FIFO) strategies, urgency-based ranking of elective patients, or waiting time-based ranking. While these schemes have shown promise in optimizing the allocation and prioritization of elective patients, there remains untapped potential in adapting similar techniques for emergency patients or using them to enhance the overall responsiveness to emergency cases.

In Table 1, some of the existing studies in the field of the OR scheduling problem pertaining to this research are briefly investigated. Based on Table 1, although the issue of group arrivals of emergency patients has not been explored in depth in previous literature, despite being a prevalent phenomenon in real-world scenarios, the present study seeks to fill this gap. By simultaneously considering elective and emergency patients, including group arrivals of emergency patients, our work offers a comprehensive approach to OR scheduling. Furthermore, we propose novel mathematical models for both initial scheduling and rescheduling, with a focus on utilizing the allocation and prioritization of elective patients to enhance the response to emergency arrivals, thereby contributing to the advancement of this field.

Table 1. Findings of the Literature Survey

Research	Modelling			Type of problem			Uncertainty aspects			Patient	
	A	B	C	D	E	F	G	H	I	J	K
Almoghrabi & Sagnol)2024)	✓			✓			✓	✓		✓	✓
Fallahpour et al. (2024)	✓			✓	✓		✓	✓		✓	✓
J. J. Wang et al. (2021)	✓				✓	✓		✓		✓	✓
Ballestín et al. (2019)	✓				✓	✓				✓	
Eshghali et al. (2024)	✓			✓	✓	✓	✓	✓		✓	✓
Lalmazloumian et al. (2023)	✓			✓			✓	✓		✓	✓
Vanberkel et al. (2011)			✓	✓						✓	
Azar et al. (2022)	✓				✓		✓			✓	
Oliveira et al. (2020)	✓				✓					✓	
Lahijanian et al. (2016)	✓				✓		✓			✓	
Miao & Wang (2021)	✓				✓	✓		✓		✓	✓
Britt et al. (2021)	✓				✓		✓			✓	
Vali-Siar et al. (2018)	✓			✓	✓		✓			✓	
Visintin et al. (2017)	✓	✓		✓			✓			✓	
Hooshmand et al. (2018)	✓				✓	✓	✓			✓	
Y. Wang et al. (2024)	✓			✓	✓		✓	✓		✓	✓
Miao & Wang (2023)	✓			✓	✓		✓	✓		✓	✓
Kamran et al. (2020)	✓				✓			✓		✓	✓
Atighehchian et al. (2020)	✓			✓	✓		✓			✓	
Choi & Wilhelm (2014)			✓	✓			✓			✓	
Akbarzadeh et al. (2019)	✓			✓	✓	✓				✓	
Anjomshoa et al. (2018)	✓			✓						✓	
Guido et al. (2018)	✓			✓						✓	
This paper	✓				✓	✓		✓	✓	✓	✓

mathematical programming (A)// simulation(B)// others(C)// planning(D)// scheduling(E)// rescheduling(F)// surgery duration(G)// arrival of emergency patients(H)// group arrivals of emergency patients(I)// elective(J)// emergency(K)

3) Problem Statement and Formulation

This paper introduces an innovative scheduling and rescheduling method for elective and emergency patients in ORs. During a typical workday, multiple elective surgeries are scheduled; however, emergencies may occur, involving either individual cases or groups of patients. In light of the requirement for an available OR to commence surgery for an emergency patient, the intricacy of managing these circumstances escalates when multiple emergency patients arrive simultaneously during the day, constituting a group arrival scenario. The finite waiting times for emergency patients compound this issue, as extended waiting periods are not feasible. If ORs are not vacated, effective management and control of such situations becomes significantly more challenging, potentially leading to the rejection of emergency patients. Although predicting the exact timing of group arrivals of emergency patients is impracticable, harnessing historical data allows us to estimate the probability of these occurrences at different intervals throughout the day (Gorgi et al., 2025).

To better manage these disruptions, we suggest dividing the workday into several time blocks, ranked based on the likelihood of the arrival of emergency patients. Since elective surgery durations are known in advance, patients with shorter procedures are assigned preferentially to time blocks with a higher probability of emergency arrivals or group arrivals of emergency patients. This allocation strategy prioritizes OR availability for emergency cases, allowing for a quicker response to emergencies. We create a scoring system to implement this approach. Elective patients with shorter surgery times receive higher scores when assigned to blocks with a greater probability of emergency arrivals. Conversely, these patients receive lower scores when assigned to blocks with a lower likelihood of emergency arrivals. By adopting this scoring mechanism and strategically allocating elective patients, we aim to improve the overall efficiency of emergency response in ORs. This method is especially beneficial when handling group emergencies, as it ensures a higher availability of ORs and expedites treatment for emergency patients by scheduling shorter elective surgeries during high-risk periods.

The division of the workday into time blocks is based on input from hospital management and a thorough analysis of historical data. In this study, we focus on a three time block configuration (Figure 1). Our approach is guided by several assumptions: each patient's surgeon is known beforehand, and the number of elective surgeries scheduled for the day is given. The surgery time of elective patients is known. All ORs are available for use from the start of the day, with each room having a capacity of one patient. Once an operation begins, it must be completed without interruption. The optimization problem's scheduling horizon is limited to a single day.

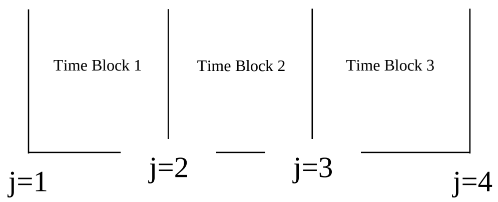


Figure 1. Three Time Block Segmentation

3.1) Scheduling and Initial Mathematical Model

At the start of the first time block (j = 1), as shown in Figure 1, initial scheduling is generated for all elective patients with the primary goal of assigning patients with shorter surgical times to blocks with a higher probability of group arrivals of emergency patients. To achieve this objective, we employ a cost-based minimization function instead of the previously described scoring system. This scheduling process involves allocating elective patients to specific time blocks and operating rooms, followed by determining their sequence. The mathematical model and associated symbols are detailed below:

Sets, indices, and parameters

I Set of elective surgeries to be scheduled, indexed by i, i'.

R Set of available ORs, indexed by r, r'.

C Set of time blocks of the working day indexed by c.

d_i The duration of surgery i (in minutes) ($\forall i$).

J Set of rescheduling points assuming that the surgical day starts at time 0, indexed by j, j'.

e_c Start time of block c ($\forall c$).

l_c End time of block c ($\forall c$).

Reg The daily regular OR-time (in minutes) beyond which the overtime is incurred. We assume that the surgical day starts at time 0.

$Over$ The maximum time (in minutes) allowed for overtime in each OR.

Cover Per minute OR overtime cost.

ca_{ic} The cost of assigning elective surgery i to block c ($\forall i, c$).

M A sufficiently large positive number.

Variables

A_{icr} Binary variable equal to 1 if surgery i is allocated to block c and OR r, and 0 otherwise ($\forall i, c, r$).

$B_{ii'r}$ Binary variable equal to 1 if surgery i and i' is allocated to OR r and surgery i precedes surgery i' (not necessarily immediately), and 0 otherwise ($\forall i, i', r{:}\ i \neq i'$).

s_i A non-negative continuous variable representing the start time of surgery I ($\forall i$).

o_r A non-negative continuous variable representing the overtime for OR r ($\forall r$).

Initial Mathematical Model:

Min $z = \sum_i \sum_c \sum_r Ca_{ic} A_{icr} + \sum_r co\, o_r$

s.t.

(1) $\sum_c \sum_r A_{icr} = 1 \qquad \forall i$

(2) $B_{ii'r} + B_{i'ir} \leq 1 \qquad \forall i, i', r{:}\ i \neq i'$

(3) $\sum_c (A_{icr} + A_{i'cr}) \leq 1 + B_{ii'r} + B_{i'ir} \qquad \forall i, i', r{:}\ i \neq i'$

(4) $\sum_c (A_{icr} - A_{i'cr}) \leq 1 - B_{ii'r} - B_{i'ir} \qquad \forall i, i', r{:}\ i \neq i'$

(5) $s_i \geq s_{i'} + d_{i'} - M(1 - \sum_r B_{i'ir}) \qquad \forall i, i'{:}\ i \neq i'$

(6) $s_i + d_i \leq Reg + Over \qquad \forall i$

(7) $s_i \geq e_c - M(1 - \sum_r A_{icr}) \qquad \forall i, c$

(8) $s_i \leq l_c + M(1 - \sum_r A_{icr}) \qquad \forall i, c$

(9) $o_r \geq s_i + d_i - Reg - M(1 - \sum_c A_{icr}) \qquad \forall i, r$

The objective function is to minimize the total cost, which comprises the cost of assigning patients to time blocks, and the overtime cost of each OR. Constraint (١) ensures that each surgery is assigned to exactly one OR and one time block. Constraints (2) to (4) of the current study, which define a precedence relation between surgeries, are equivalent to constraints (3) to (5) presented in the study of Hooshmand et al. (2018). Constraint sets (2) and (3) ensure that if surgeries i and i' are assigned to the same OR, then a precedence relation exists between i and i'. Constraint set (4), together with constraint set (1), implies that if a precedence relation is defined between surgeries i and i', then they must be assigned to the same OR. Constraints (5) to (8) focus on the determination of the start times of surgeries for patients. Constraint (6) guarantees that all surgeries will be completed before the end of the day (regular time plus overtime). Constraints (7) and (8) specify that if a surgery is assigned to a particular time block, its start time must fall within that time block. Constraint (9) specifies the amount of overtime for each operating room.

3.2) Rescheduling

At the onset of each time block, a scheduling must be determined. Specifically, at the beginning of the first block, an initial scheduling is created, while subsequent blocks require rescheduling if an emergency has occurred in the preceding block. At the commencement of each block, rescheduling for the remainder of the day is performed based on the recorded real-time information. Finally, after the last block, total costs are calculated, and elective patients whose surgeries have been rescheduled for the following day are identified. The mathematical models for rescheduling are outlined below:

3.2.1) First Rescheduling Model

At the onset of the second time block (j = 2), rescheduling for the remainder of the day is performed based on the actual information recorded in the first block. During this process, it is determined which surgeries, as outlined in the initial scheduling, have commenced in the first block. In this context, the completion of a surgery is equivalent to its initiation, as we assume that once started, a surgery will not be interrupted and will proceed until completion. To capture this information, we introduce a binary parameter, α_{icr}, which indicates whether surgeries included in the initial scheduling of the first block have started or not. Specifically, at the beginning of the second block, α_{icr} is determined for $c = c1$ and for all i and r. The value of α_{ic_1r} will be equal to 1 if surgery i has started in room r during the first block, and 0 if surgery i has not commenced in room r during the first block. Consequently, at the commencement of the second block, the value of α_{ic_1r} is determined, and the first rescheduling is executed. Surgeries with $\alpha_{ic_1r} = 0$ will remain in the scheduling, while those with $\alpha_{ic_1r} = 1$ will be excluded. In the following, the mentioned mathematical model is presented.

We consider all sets, indices, and parameters of the initial mathematical model, plus the following:

C' Set of time blocks before $j = 2$, indexed by c'; $\mathrm{c}' = \mathrm{c}_1$

C'' Set of all time blocks mines C', indexed by c''; $\mathrm{c}'' = \mathrm{c}_2, \mathrm{c}_3$

$\alpha_{ic'r}$=1 if the actual start time of surgery i is in block c' and OR r

co' Cost of shifting a surgery to the next day

Additionally, by adding the following variable to all the previous variables, the variables of this step are determined.

$\mathrm{o}'(i)$ is the non negative variable that represents the amount of time surgery takes after regular time and overtime. In other words, a positive value for this variable indicates that the surgery has been rescheduled to the next day.

First Rescheduling Mathematical Model:

Min $\quad z = \sum_i \sum_c \sum_r Ca_{ic} A_{icr} + \sum_r co\ o_r + \sum_i co'\ o'_i$

s.t.

(1)-(5), (7), (9)

(10) $\quad s_i \le l_{c''} + M(1 - \sum_r A_{ic''r}) \qquad \forall i, i''$

(11) $\quad A_{ic'r} \ge 1 - M(1 - \alpha_{ic'r}) \qquad \forall i, c', r$

(12) $\quad A_{ic'r} \le M\alpha_{ic'r} \qquad \forall i, c', r$

(13) $\quad o'_i \ge s_i + d_i - (Reg + Over) - M(1 - \sum_c A_{icr}) \qquad \forall i, r$

The objective function is to minimize the total cost, which comprises the cost of assigning patients to time blocks, the overtime cost of each OR, and the cost of surgery time exceeding the working day. Constraint (10) specify that if a surgery is assigned to a particular time block, its start time must be before that time block. Constraints (11) and (12) ensure that if a surgery has been performed before this time, it will be left out of the scheduling. And Constraint (13) specifies how much the patients' surgery time exceeds the working day.

3.2.2) Second Rescheduling Mathematical Model

Upon reaching the beginning of the third time block (j = 3), we must establish the values of $\alpha_{ic'r}$ for $C' = 1{,}2$ and reschedule for the remainder of the day. The modeling approach for this stage closely mirrors the previous stage's methodology. We utilize the same sets, indexes, parameters, and variables as the previous step, except set C', which now includes the values c_1 and c_2. The mathematical modeling for this stage can be formulated as follows:

Second Rescheduling Mathematical Model:

Min $\quad z = \sum_i \sum_c \sum_r Ca_{ic} A_{icr} + \sum_r co\, o_r + \sum_i co'\, o'_i$

s.t.

(1)-(5), (7), (9)-(13)

3.3) End of the Working Day

At the conclusion of the workday (j = 4), it is necessary to calculate all relevant costs, encompassing the overtime costs for each operating room and the costs associated with transferring elective patients to the following day. Therefore, in this step, only the value of the following expression should be specified:

$$\sum_r co\, o_r + \sum_i c_{shift}(1 - \sum_c \sum_r \alpha_{icr})$$

4) Solution Method

The mathematical models proposed in this study can be categorized as flexible job shop problems, a class of NP-Hard problems (Fattahi et al., 2007). Consequently, for larger-scale models, an approximate solution method with reasonable computational time is required. To address this, we adapt and apply the invasive weed optimization algorithm (IWO), an intelligent, evolutionary optimization technique inspired by the processes of reproduction, survival, and adaptability observed in weeds (Mehrabian & Lucas, 2006).

In our problem, the surgery duration of elective patients is the key factor influencing the schedules. Therefore, each plant in IWO represents a permutation of the patient's surgery times, as illustrated in the first row of Table 2. In this table, rows 2 to 4 depict the patient's cost for time blocks 1 to 3, respectively. For instance, it is assumed that the second time block has a higher probability of group arrivals and more emergency patients compared to the other two blocks, followed by the third and first blocks.

Table 2. Weed Structure of the Problem

	1	2	3	…	I
D	72	130	100	…	83
c1	100	0	75	…	100
c2	0	100	75	…	0
c3	50	50	0	…	50

According to Table 2, the first patient has a shorter surgery time than others, making it preferable to assign them to the second block. Consequently, the cost of allocating this patient to the second block is 0, whereas assigning them to blocks 3 and 1 incurs costs of 50 and 100, respectively. This demonstrates that allocating the patient to the first block would result in significantly higher costs. Following the same rationale, allocation costs for the remaining patients are determined using this approach. Figure 2 demonstrates the pseudo-code of the proposed IWO.

Iter=0
Initialize population P
Evaluate (P(Iter))
While not converged ‖ max Iterates do
Seed$_p$(Iter)=Seed Calculation(Iter)
Calculation (P(Iter)
Dispersion$_p$(Iter)=Seed Dispersion Calculation(Iter)
P$_s$(Iter)=reproduction(Seed$_p$(Iter), Iter=Iter+1, Dispersion$_p$(Iter))
Evaluate (P$_s$(Iter))
P(Iter+1)=Next Generation(P$_s$(Iter), P(Iter))
Iter=Iter+1
End

Figure 2. The Pseudo-Code of IWO Steps

5) Computational Experiments

This section evaluates the proposed mathematical models and algorithm using a series of randomly generated test problems. Section 5.1 outlines the method used for generating these problems, while Section 5.2 provides the parameter settings for IWO. Finally, Section 5.3 presents the computational results obtained through the proposed approaches on these instances. Experiments were conducted on a Windows 10 PC, equipped with a Core(TM) i5 processor, running at 2.4GHz and featuring 8GB of RAM. The implementation of IWO was achieved through MATLAB software. For smaller problems, the CPLEX method was utilized.

5.1) Test Problems

Due to the lack of access to real-world data, test problems have been generated according to Hooshmand et al. (2018) and Leeftink and Hans (2018) , whose specifications are as follows:

- The number of operating rooms has been set to 2, 5, 10, 15, 20, 25, 30, 35, and 40 effectively covering a range of small, medium, and large instances suitable for assessing the proposed models and IWO.
- The surgeon's workday commences at time 0, with legal and overtime durations of 480 and 120 minutes, respectively, for each operating room. The time basis for rescheduling is 160 minutes for the first rescheduling and 320 minutes for the second rescheduling. Total costs and patients transferred to the next day are determined at the end of the day (600 minutes).
- The number of elective patients scheduled for surgery ranges from 10 to 192, depending on the problem size.
- The surgery time of elective patients is randomly selected within the range of 50 to 200 minutes.

The cost allocation for elective patients in time blocks is determined as follows:

- The allocation cost ranges from 0 to 100, taking into account the elective patient's surgery time, the probability of group entry, and the number of emergency patients in each time block. Consequently, for patients with surgery times close to 50 minutes, the allocation cost approaches zero for blocks with lower probabilities of group entry and a higher number of emergency patients, while the cost nears 100 for blocks with higher probabilities of group entry and fewer emergency patients. The cost allocation for other time blocks remains close to 50. Conversely, for patients with surgery times closer to 200 minutes, the high-value assignments for the first two time blocks are reversed, while the third block allocation cost remains near 50.

- Probability of group emergency arrivals: To account for varying likelihoods of group emergency patient arrivals, different time blocks have been assigned distinct probabilities. These probabilities are determined based on historical data, expert insights, or other relevant factors.

The validation of this method and the initial mathematical model are discussed in the following section.

5.1.2) Validation of Test Problem Generation Method and Initial Mathematical Model

In this section, we will analyze and evaluate Test Problem 1, which has been generated using the proposed test problem generation method detailed in the previous section. We also provide the solution obtained using the CPLEX method. The surgery times of randomly selected patients are presented in Table 3. It can be observed that patients numbered 5, 6, 7, 8, 9, and 10 have longer surgery times than others. Due to the assumption that the likelihood of group arrivals of emergency patients increases from Time Block 2 to 3 and then to 1, it would be better not to assign these patients to Time Block 2. Instead, assigning patients numbered 1, 2, 3, and 4 to Time Block 2 is recommended.

The corresponding allocation costs for patients to time blocks are presented in Table 3. Given the problem specifications and the optimal solution acquired from the exact solution method (Figure 3), it can be inferred that the test problem generation method outlined in the previous section, as well as the initial scheduling mathematical model detailed in Section 3.1, are valid and exhibit sufficient reliability. Larger problem instances have been developed based on this problem.

Table 3. Surgery Times of Patients in Test Problem 1

Patient	Duration
1	72
2	75
3	80
4	60
5	90
6	85
7	120
8	130
9	200
10	110

Table 4. Costs of Assigning Patients to Time Blocks in Test Problem 1

Patient	Time Block 1	Time Block 2	Time Block 3
1	100	0	50
2	100	0	50
3	100	0	50
4	100	0	50
5	50	100	0
6	50	100	0
7	0	100	50
8	0	100	50
9	0	100	50
10	50	100	0

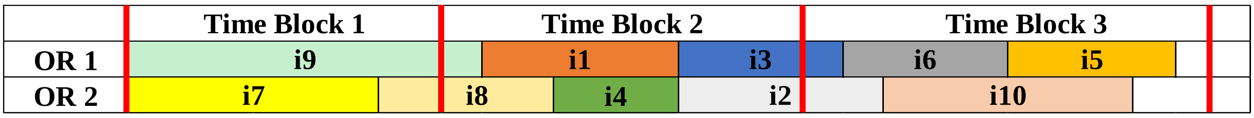


Figure 3. Optimal Answer in Test Problem 1

Referring to Figure 3, there are four patients in Time Block 2 with shorter surgery times compared to other patients. Since the probability of a group of emergency patients arriving in this block is higher, if such an event occurs, the operating rooms are likely to be vacated more quickly due to the shorter surgery times of the elective patients. By employing this strategy, we can better manage group and individual emergency patient arrivals during certain periods of the day. Given the lower probability of group emergency patient arrivals in Time Blocks 3 and 1, patient allocation is more flexible, with patients requiring longer surgery times being assigned to these blocks.

5.2) Tuning the IWO Parameters

This section details the parameter selection for the IWO algorithm, which is crucial for executing the proposed scheduling strategy. The PopSize, Smin, Smax, and Exponent parameters have been calibrated using the Taguchi method, a widely applied systematic approach for optimizing metaheuristic parameters. The values of PopSize, Smin, Smax, and Exponent are set to 8 × |I|, 1, 7, and 3, respectively. For further information on the Taguchi method's application, refer to section 5.2.1.

The less impactful parameters Max It, Sigma Initial, and Sigma Final are assigned values of 100, 1, and 0.001, respectively. The Taguchi method is preferred for parameter calibration due to its simplicity and effectiveness, as demonstrated by its use in various research (Candan & Yazgan, 2015). An in-depth description of the Taguchi method can be found in Roy (2001).

5.2.1) Tuning IWO Parameters by the Taguchi Method

This section outlines the process of calibrating the Popsize, Smin, Smax, and Exponent parameters in the IWO algorithm using the Taguchi method. Table 4 summarizes the various levels of parameters to be considered.

Table 4 includes three levels 2×|I|, 4×|I|, and 8×|I| for the Popsize parameter, representing 2, 4, and 8 times the plant's length, respectively. Rather than examining all 81(34) combinations of parameter levels, the Taguchi method suggests employing the orthogonal array L9(34), presented in Table 5. In this table, numbers 1, 2, and 3 correspond to the levels from Table 4.

A sample problem involving initial scheduling with ten ORs and forty elective patients is utilized for the experiments. Each experiment is repeated five times to obtain valid data. According to each experiment in Table 5, the signal-to-noise (S/N) ratio is calculated using the following equation, where K represents the number of repetitions for each experiment (five in this case), and f_k value is the best solution obtained from the kth IWO run for the corresponding experiment.

$$\text{S/N ratio} = -10 \times \log\left(\frac{1}{k}\sum_{k=1}^{K} f_k^2\right)$$

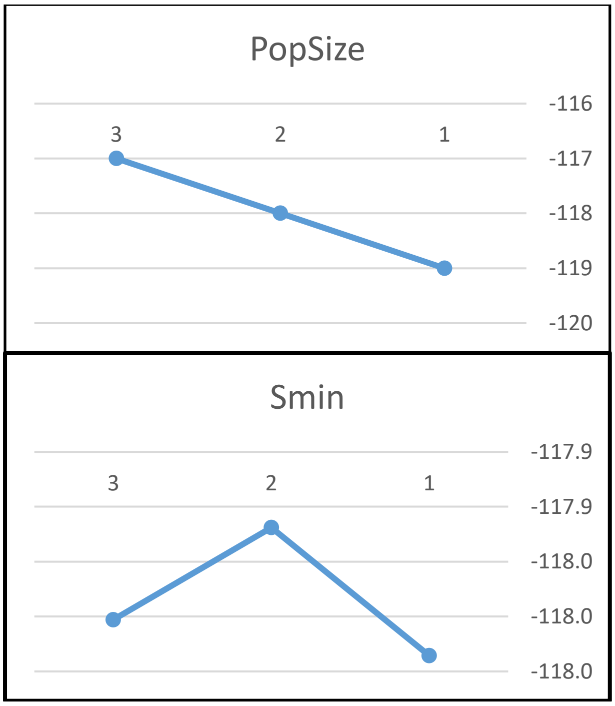
The average S/N ratio for each level of each parameter is calculated and displayed in Figure 4. A higher S/N ratio signifies better performance; therefore, the optimal values for popsize, Smin, Smax, and exponent parameters are 8×|I| (Level 3), 1 (Level 2), 7 (Level 2), and 3 (Level 3), respectively.

Table 4. Parameters and Their Levels

Parameter	Levels		
	Level 1	Level 2	Level 3
PopSize	2×|I|	4×|I|	8×|I|
Smin	0	1	2
Smax	5	7	10
exponent	1	2	3

Table 5. The Orthogonal Array L9(34) and the S/N Ratios

Experiment	Parameters				S/N ratio
	PopSize	Smin	Smax	exponent	
1	1	1	1	1	-120.05
2	1	2	2	2	-118.56
3	1	3	3	3	-117.37
4	2	1	2	3	-116.49
5	2	2	3	1	-118.50
6	2	3	1	2	-118.48
7	3	1	3	2	-117.44
8	3	2	1	3	-116.78
9	3	3	2	1	-118.09



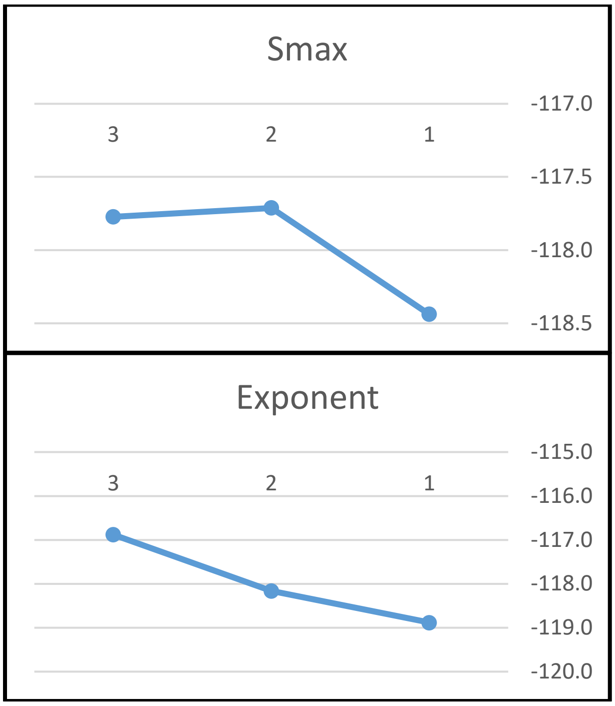


Figure 4. The Mean S/N Ratio Plot.

5.3) Computational Results

The computational results are summarized in Table 6. The columns labeled |I| and |R| denote the problem specifications, where |I| represents the number of elective patients, and |R| indicates the number of available ORs. For each test problem, three instances are randomly generated, and the average results are reported. The column labeled zCPLEX represents the objective function value obtained by CPLEX within a time limit of 10,000 seconds. An asterisk (*) signifies that the solver achieved an optimal solution for all instances in that row, while a dash (-) indicates that the solver could not find any feasible solution within the given time limit. Additionally, the column labeled zIWO displays the objective function value of the solution provided by the IWO method.

Table 6. Computational results for small, moderate, and large sized test problems (three instances in each row)

Row	Characteristics		Objective value			CPU time (s)	
	I	R	CPLEX	IWO	GAP(%)	CPLEX	IWO
1	10	2	6200	6200	0/00	531	15
2	10	3	0	0	0/00	1	12
3	12	2	21750	21800	0/23	1001	26
4	12	3	50	50	0/00	3	36
5	15	3	2600	2650	1/92	1007	73
6	15	4	50	50	0/00	6	48
7	17	3	18750	18800	0/27	1012	95

Row	Characteristics		Objective value			CPU time (s)	
8	17	4	100	100	0/00	37	108
9	20	4	1700	1700	0/00	2560	142
10	20	5	50	50	0/00	50	120
11	25	5	1500	1400	-6/67	>10000	150
12	25	6	100	150	50/00	880	241
13	30	6	8000	7700	-3/75	>10000	284
14	30	7	150	50	-66/67	>10000	350
15	35	7	-	16850	-	>10000	480
16	35	8	-	100	-	>10000	492
17	40	8	-	20950	-	>10000	610
18	40	9	-	200	-	>10000	572
19	48	10	-	12850	-	>10000	601
20	72	15	-	23500	-	>10000	725
21	99	20	-	71250	-	>10000	884
22	120	25	-	84125	-	>10000	1001
23	147	30	-	151250	-	>10000	1501
24	171	35	-	182750	-	>10000	2136
25	192	40	-	200325	-	>10000	3024

The column labeled GAP(%) illustrates the percentage difference between these two objective function values, calculated using the following formula.

$$\frac{z^{IWO} - z^{CPLEX}}{z^{CPLEX}} \times 100$$

The final two columns depict the average time associated with CPLEX and IWO, measured in seconds. Note that in the column representing the CPU time of the CPLEX, the mark '>' indicates that for some or all instances of the corresponding test problem, the CPLEX could not terminate within the time limit. According to the data presented in Table 6, the discrepancy between the objective function values obtained from the optimal CPLEX solution and the IWO method in rows 1 to 10 and 12 is notably minimal. Specifically, the maximum difference observed between the objective functions is 50. Furthermore, for test problems 11, 13, and 14, the negative Gap values demonstrate that, on average, the IWO approach yields superior solutions when compared to the feasible solutions provided by CPLEX within the mentioned time limit. As demonstrated in rows 15 to 25, CPLEX is unable to identify a feasible solution within the mentioned time limit for these problems. Consequently, only the IWO solution method proves suitable and efficient in yielding an approximate solution within a reasonable time frame. By examining the difference between zIWO and zCPLEX outcomes in small and medium-sized problems, it is evident that IWO consistently achieves results that closely approximate the optimal solution. Consequently, it can be concluded that IWO's solutions for large-scale problems can be considered near-optimal. This observation underscores the high efficiency of the IWO algorithm.

A significant observation is the substantial reduction in costs associated with an increase in the number of ORs. As indicated by the obtained values, in certain instances, the cost approaches zero as additional OR are introduced.

6) Conclusion

This study addresses the challenge of integrating scheduling and rescheduling for both elective and emergency patients in operating rooms. The allocation and sequencing of elective patients are determined in the initial scheduling, which should be prepared at the beginning of the working day. However, emergency patients may arrive individually or in groups throughout the day, necessitating a suitable strategy in the initial scheduling to account for potential errors and disruptions that could arise from group arrivals of emergency patients. The proposed strategy involves dividing the working day into multiple time blocks based on the probability of group arrivals during each block. By doing so, time blocks with higher probabilities of group arrivals are identified, enabling a more effective allocation of elective patients. Particularly, elective patients with shorter surgery times are allocated to time blocks with a higher likelihood of group arrivals of emergency patients, as their surgeries are completed more quickly, allowing for prompt initiation of emergency surgeries. Consequently, this strategy assigns patients with shorter surgery times to higher-risk time blocks, while those with longer surgery times are allocated to blocks with a lower probability of group arrivals. This strategy proves effective not only for group arrivals but also for individual emergency patient arrivals.

At the start of the first time block, an initial scheduling mathematical model is applied, and at the beginning of subsequent blocks, a rescheduling mathematical model is employed. At the end of the working day, all costs are calculated, and patients who need to be transferred to the next day are identified. The IWO algorithm is utilized to solve large-scale instances of this NP-hard optimization problem. Computational experiments, conducted on a series of randomly generated test problems, demonstrate the efficacy of the IWO algorithm in terms of both solution quality and computation time.

Eventually, several avenues for future research are suggested. One potential direction is to examine the division of time blocks and their durations more closely, potentially utilizing machine learning techniques to predict the number of emergency arrivals in each block (Karami, 2022). Further research could also incorporate additional uncertain conditions, such as surgery times for elective patients. Moreover, it would be beneficial to compare the efficiency of the proposed algorithm with other existing approaches and explore opportunities for further development and improvement.

Declarations

Ethical Approval and Consent to Participate: Not applicable. The only data used were for generating the test problems, based on the work of the two articles referenced in Section 5.1. This procedure ensured compliance with ethical guidelines and regulations, making ethical approval unnecessary.

Competing Interests: The authors declare no competing interests.

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