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A Simulation-Based Optimization Evaluation of Operating Room in Healthcare under Limitation Capacity: A Multi-objective Approaches

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ABSTRACT

Operating room scheduling comprises determining the specific start timings for surgeries and allocating the necessary resources to each scheduled surgery. It takes into account multiple limitations to ensure a comprehensive surgical process, including the availability of resources, specialties, and restrictions. Several surgeons have different specialties, and each has a waiting list of patients whose surgeries must be scheduled on the days the surgeons are in one of the operating rooms. In addressing this matter, two objectives are taken into account: minimizing expenses associated with overtime and unutilized operating rooms, while maximizing the number of days patients wait for surgery. The resolution of this problem involves two approaches: mathematical modeling and optimization through simulation-based methods. The findings indicate that when addressing the operating room scheduling issue, the simulation-based optimization solution matches the quality of the solution provided by the mathematical model for smaller problems and offers a timely and satisfactory solution for larger-scale problems.

1. Introduction

Surgical care presents one of the primary areas where healthcare providers encounter significant challenges in terms of resource allocation, expenses, and income generation, the operating room serves as the central hub, constituting approximately 65% of hospital admissions. Conversely, it stands out as one of the costliest departments within hospital budgets, representing around 35% of total hospital costs. Operating rooms have the largest share in the costs of any hospital and, on the other hand, its income. Although surgeries and patient types vary, the typical procedure for patient visits follows this pattern: Initially, patients are prepared for surgery either randomly (in the case of emergency patients) or based on scheduled appointment times (for selected patients). Once the designated operating room becomes available, the patient is moved to that room. Following the surgery, the patient is transferred to the recovery room and subsequently to either a general ward, specialized care unit, or emergency department.

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Scheduling operating rooms means determining the day of surgery, the sequence of surgeries, and the time of each in a day and allocating required resources (such as surgeons, anesthesiologists, and equipment) according to the existing limitations [1]. Meanwhile, multiple and occasionally conflicting objectives need to be fulfilled, with the primary aim of enhancing patient service levels while concurrently lowering hospital expenses. The probabilities of events such as patient arrival times, duration of surgeries, availability of operating room staff and other resources, and the time required for operating room preparation further complicate the issue [2]. The tendency to use simulation and meta-engineering optimization algorithms can be seen in recent research. Numerous researchers have drawn parallels between operating room planning and scheduling challenges and established optimization problems. Examples include likening the allocation of surgeries to packaging problems, scheduling surgeries while accounting for preparation time, allocating work to parallel machines, and adopting an open approach to scheduling akin to dividing sets. Various objective functions have been explored for scheduling operating rooms [3]. Prolonged waiting times for surgery stand out as a typical patient grievance. Lengthening queues for medical services in hospitals, particularly for surgeries, not only risks exacerbating patients' conditions due to delayed treatment but may also discourage them from seeking care altogether, worsening their situations [4]. Reducing patient waiting time serves as a key criterion for identifying an optimal schedule. Additionally, the hospital incurs expenses for the entire duration that operating rooms and surgical teams remain available. Thus, minimizing idle time is ideal to avoid unnecessary costs. However, achieving complete elimination of idle time is impractical due to the unpredictable nature of events, which necessitates schedule adjustments. Moreover, overloading a single day with numerous operations to minimize idle time risks incomplete procedures within regular working hours [5]. As a result, resources have to stay in the hospital for more hours. Typically, operating room overtime leads to an increase in hospital costs. Costs resulting from both idle time and overtime are overhead costs. While the hospital's expenditure on employee salaries during surgery hours remains fixed, costs stemming from idle time or overtime in operating rooms are controllable through proper scheduling. Therefore, minimizing idle time and overtime among operating room staff stands as a crucial criterion in assessing a schedule's effectiveness.

Various mathematical models have been prepared to describe various forms of the operating room scheduling problem. Bre et al. [6] devised a straightforward model outlining their approach to assigning surgeries across a planning horizon (e.g., a week) to various time slots (e.g., days of the week). Similarly, [7] constructed a basic model for concurrently assigning operating rooms to surgeons and their respective patients to minimize hospital costs and patient waiting times. The duration of surgeries and the arrival of non-elective patients represent two unpredictable and stochastic events that significantly influence the efficiency of operating rooms [8-9]. The key to effectively managing them lies in employing appropriate scheduling strategies for surgeries. While there are additional uncertainties within the system, such as potential delays for selected patients or the surgical team, alternative methods can often mitigate these occurrences, which typically have minimal impact on operations. Some studies have also examined these random variables in their research. The multitude of complexities inherent in the problem, particularly the occurrence of various events, has sparked a surge in utilizing simulation as a means to tackle it [10-12]. In recent times, simulation has not only been employed for scenario analysis but has also been utilized in optimization approaches. In studies comparing the problem of sequencing surgeries across multiple rooms, akin to parallel machine scheduling, simulation-based methods have been examined alongside simpler sequencing strategies [13]. In another study, the preparation time for operating rooms has been distinguished from the duration of surgeries and linked to subsequent operations.

Another study introduced a simulation-based optimization tool utilizing the meta-heuristic approach of simulated annealing [14].

This research involved constructing a simulation-based model for an outpatient surgery center with the aim of minimizing wait times and patient dropout rates. Three optimizers were developed, all utilizing the simulated annealing algorithm. The distinction lies in that the initial solution for two of them is derived from a mathematical model. Another study implemented a two-stage scheduling simulation: initially assigning surgeries to specific rooms, followed by determining the sequence of surgeries within each room. The timing in this approach wasn't driven by optimization but rather by employing an innovative and distinct algorithm across various scenarios, with the results of these scenarios subsequently compared. In addressing the operating room scheduling problem, optimization, scenario analysis, and problem complexity analysis stand out as the most crucial methodologies. Optimization endeavors to identify solutions that either precisely or approximately maximize the objective function. On the other hand, scenario analysis aims solely to evaluate the performance across various system configurations. The complexity analysis approach, albeit present in a limited number of studies, delves into scrutinizing the intricacies of operating room scheduling problems or the proposed solutions. For instance, research introducing and formulating a problem aimed at reducing the waiting time for emergency patients demonstrated that this problem falls under the category of NP-hard. The selection of problem-solving method is another critical aspect to consider in research methodology. Mathematical planning and its exact solution methods, heuristic and meta-heuristic methods, as well as simulation, are utilized to address surgery scheduling problems. It's evident that the selection of an appropriate method depends on the research approach. For instance, simulation is often more suitable for conducting scenario analysis.

Based on these explanations, several recent articles addressing operating room scheduling can be classified as shown in Table 1.

Table 1
The review of various methods based on the operating room in healthcare

Authors	Patient's type		Objective Function			Methodology				Uncertainty		Application				Solution approaches		
	Normal	Emergency	Waiting time	Extra Work	unemployed	MILP	Fuzzy analysis	Stochastic	optimization	Yes	No	Sequencing	Room selection	Day determining	Capacity level	Simulation	Heuristic	Metaheuristic
Niu et al. [15]		*		*	*	*		*			*	*		*				*
Wooley et al. [16]	*			*	*		*	*		*		*	*				*	*
Wang et al. [17]		*	*			*	*			*		*		*		*		
Persson et al. [18]		*		*				*	*		*	*		*			*	
Peng et al. [19]		*						*	*		*	*					*	
Eshghali et al. [20]	*		*		*	*				*			*	*			*	
This research	*	*	*	*	*	*			*	*		*	*		*	*	*	*

This classification draws inspiration from existing categorizations. While it may be incomplete, it does shed light on some distinctions between current and previous research. Notably, the utilization of novel methods to tackle multi-criteria optimization problems in operating room scheduling appears to be a relatively emerging area of focus.

The contribution and novelties of this research are as follows:

i. Considering the impact of surgeons' skill levels during surgeries is crucial. Surgeons' proficiency is a predictable factor that can significantly influence procedure durations, thereby affecting scheduling. However, despite reviews, none of the prior research has addressed this factor in operating room scheduling.
ii. We considered the simultaneous use of two methods of mathematical modeling and simulation-based optimization and compared these methods with each other in the issue of operating room scheduling.
iii. Two metaheuristic algorithm approaches, defined as the multi-objective evolutionary algorithm (MOEA) and NSGA-II, are proposed, where each solution evaluation is computationally and financially expensive to assess uncertainty based on limited resources.

The rest of this paper is organized as follows. Section 2 discusses the methodology and problem statement. Section 3 outlines the solution approaches, and introduces the two various optimization algorithms model. Section 4 presents comparative findings among various optimization methods. Section 5 proposes about discussion and some implications related to gaps and limitations. Lastly, Section 6 provides concluding remarks and outlines future directions.

2. Methodology

2.1. Problem Statement

In this research, to enhance its applicability, we selected a public hospital in Shanghai as our study site, aiming to develop a model based on a real-world scenario. Each of the 60 surgeons at this hospital is available for surgery on specific days of the week, operating only on those days as per the schedule managed by the operating room administration. However, there is no fixed assignment of a particular room to a specific surgeon on any given day. Instead, the hospital allocates its 10 operating rooms to surgical groups, each consisting of several surgeons, throughout the week. After a patient consult with a surgeon and surgery is deemed necessary, the patient's name and the type of operation are communicated to the operating room management. Each day, the operating room finalizes the schedule for surgeries scheduled for the following day. Surgeons then announce and allocate rooms and shifts for these surgeries. Figure 1 shows a view of this process.

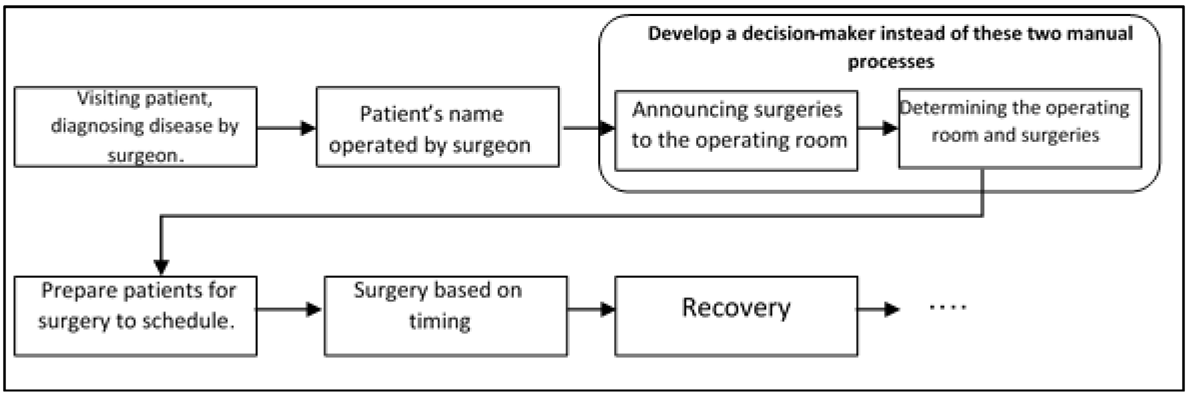

Fig. 1. The framework of the surgical process of patients in the operating room of the hospital.

The scheduling of the operation rooms in this hospital aims to achieve two primary objectives: Firstly, to minimize the overall costs resulting from nurses' and doctors' underemployment or overtime in the operating rooms. Secondly, to reduce patient waiting times. Assuming all patients are equally prioritized, the second objective can be viewed as maximizing the number of surgeries performed per day.

2.2. Mathematic Model

2.2.1. Assumptions

To prepare the mathematical model of this problem, we add the following assumptions to the mentioned facts:

i. As someone in a position to make decisions, the operating room supervisor must determine whether all patients will undergo surgery on the same day.
ii. The planning and scheduling remain unchanged. This entails no cancellations, additions, or alterations to the operating room schedule or sequence.
iii. Patients and surgeons must be available from the beginning of the scheduling period (specified day).
iv. Each surgery requires only one surgeon, along with the anesthesia team and nurses, to perform the surgery.
v. Apart from the surgeon and the operating room, all necessary resources including recovery beds and special care facilities are sufficiently available, ensuring surgeries are not delayed due to resource constraints.
vi. The duration of the operation, including associated pre- and post-operative procedures within the operating room, as well as the recovery time, are predetermined and consistent for each patient.
vii. The total anticipated duration of surgeries scheduled during an operating room session must be at most its allocated time frame.

In regard to the underlying assumptions of the problem, it is crucial to note that the duration of each surgery primarily hinges on the surgeon's expertise and the nature of the procedure. Surgeries typically range from approximately 40 minutes to nearly 6 hours, with the recovery period also contingent upon the type of operation. Given that the surgeon and the type of operation are already identified, we can naturally anticipate this variability in advance. All research conducted for this study is based on data reviewed from Shanghai Children's Hospital. In order to develop our optimization model, we present the following indices, parameters, and decision variables.

Indices:

$o \in O$	number of operating rooms
$p \in P$	number of patients
$s \in S$	number of surgeons
$t \in T$	period of time

Parameters:

T_o	twice the regular cost is incurred for each additional hour of overtime in the operating room
I_o	the cost of each hour of idle time in the operating room
A_s	availability of surgeon equal to 1 or unavailability of 0 surgeon *s*

$\boldsymbol{Pro_{po}}$	the probability of patient *p* being operated on is equal to 1 or the impossibility of 0 in the operating room *o*
$\boldsymbol{t_p}$	the duration of the patient's surgery *p*
$\boldsymbol{r_p}$	the duration of the patient's recovery *p*
$\boldsymbol{H_o}$	normal working hours of the operating room,
$\boldsymbol{H_s^{max}}$	the surgery time limit for surgeon *s* in one day
$\boldsymbol{tar_o^{max}}$	overtime limit for operating room *o* in one day
$\boldsymbol{Pat_s}$	patients of surgeon *s*
$\boldsymbol{tar_o}$	operating room *o* overtime for surgeons
$\boldsymbol{ct_p}$	the duration of patient *p* surgery
$\boldsymbol{Idl_o}$	idle period of operating room *o* when patients are not in surgery

Decision variables:

$\boldsymbol{X_{po}}$	if patient *p* is operated on in operating room *o*, equal to 0; otherwise 1
$\boldsymbol{ss_{pp'}}$	if patient *p* is operated on immediately after patient *p'* in the surgical sequence it equals 1; otherwise, it is 0 (that is, both patients belong to the same surgeon)
$\boldsymbol{SS_{p,p+1}}$	if patient *p* is selected in the sequence of the surgeon for the first/last surgery, equal to 1; otherwise 0
$\boldsymbol{SS_{0,p+1,s}}$	If none of the patients of surgeon *s* are operated on, it is equal to 1. Otherwise, those who are operated on is equal to 0,
$\boldsymbol{sr_{p'po}}$	If patient p is operated in the operating room sequence immediately after patient p, it is equal to 1, otherwise 0,
$\boldsymbol{SS_{p,p+1,o}}$	If patient p is placed in the sequence of an operating room o as the first/last surgery, it is equal to 1 and otherwise, 0,
$\boldsymbol{SS_{0,p+1,o}}$	If no patient is operated on in the operating room o, it equals 1. Otherwise, some are operated on 0,

The mathematical programming model for operating room in healthcare under limitation capacity can be represented as follows using the above notations:

$$\min \sum_{o=1}^{O}(T_o tar_o + I_o idl_o) \tag{1}$$

$$\max \sum_{p=1}^{P}\sum_{o=1}^{O} X_{po} \tag{2}$$

subject to

$$\sum_{o=1}^{O} x_{po} \leq A_s \quad \forall S \in \{1,\ldots,S\}, p \in Pat_s \tag{3}$$

$$x_{po} \leq Pos_{po} \quad \forall p \in \{1,\ldots,P\}, o \in \{1,\ldots,O\} \tag{4}$$

$$\sum_{p \in Pat_s}\sum_{o=1}^{O} x_{po} t_p \leq H_s^{\max} \quad \forall s \in \{1,\ldots,S\} \tag{5}$$

$$\sum_{o=1}^{O} x_{po} = SS_{0p} + \sum_{p' \in Pat_s, p' \neq p} SS_{p'p} \quad \forall s \in \{1,...,S\}, p \in Pat_s \tag{6}$$

$$\sum_{o=1}^{O} x_{po} = \sum_{p' \in Pat_s, p' \neq p} SS_{p'p} + SS_{p,p+1} \quad \forall s \in \{1,...,S\}, p \in Pat_s \tag{7}$$

$$\sum_{p \in Pat_s} SS_{0p} + SS_{0,p+1,s} = 1 \quad \forall s \in \{1,...,S\} \tag{8}$$

$$SS_{0,p+1,s} + \sum_{p \in Pat_s} SS_{p,p+1} = 1 \quad \forall s \in \{1,...,S\} \tag{9}$$

$$x_{po} = \sum_{p'=0, p' \neq p}^{P} sr_{p'po} \quad \forall p \in \{1,...,P\}, o \in \{1,...,O\} \tag{10}$$

$$x_{po} = \sum_{p'=1, p' \neq p}^{P+1} sr_{pp'o} \quad \forall p \in \{1,...,P\}, o \in \{1,...,O\} \tag{11}$$

$$\sum_{p=1}^{P+1} sr_{0po} = 1 \quad \forall o \in \{1,...,O\} \tag{12}$$

$$\sum_{p=0}^{P} sr_{p,p+1,o} = 1 \quad \forall o \in \{1,...,O\} \tag{13}$$

$$ct_p \geq t_p + ct_{p'} + r_{p'} + (ss_{p'p} - 1)M \quad \forall s \in \{1,...,S\}, p, p' \in Pat_s, p' \neq p \tag{14}$$

$$ct_p \geq t_p + (ss_{0ps} - 1)M \quad \forall s \in \{1,...,S\}, p \in Pat_s \tag{15}$$

$$ct_p \geq t_p + ct_{p'} + (ss_{p'p} - 1)M \quad \forall o \in \{1,...,O\}, p, p' \in \{1,...,P\}, p' \neq p \tag{16}$$

$$ct_p \geq t_p + (ss_{0po} - 1)M \quad \forall o \in \{1,...,O\}, p \in \{1,...,P\} \tag{17}$$

$$tar_o \geq ct_p + (x_{po} - 1)M - H_o \quad \forall p \in \{1,...,P\}, o \in \{1,...,O\} \tag{18}$$

$$idl_o \geq H_o + tar_o - \sum_{p=1}^{P} x_{po} t_p \quad \forall o \in \{1,...,O\} \tag{19}$$

$$idl_o, tar_o \geq 0 \quad \forall o \in \{1,...,O\} \tag{20}$$

$$tar_o \leq tar_o^{\max} \quad \forall o \in \{1,...,O\} \tag{21}$$

$$x_{po} \in \{0,1\} \quad \forall p \in \{1,...,P\}, o \in \{1,...,O\} \tag{22}$$

$$ss_{p'p} \in \{0,1\} \quad \forall s \in \{1,...,S\}, p, p' \in Pat_s, p' \neq p \tag{23}$$

$$ss_{0ps} \in \{0,1\} \quad \forall s \in \{1,...,S\}, p \in Pat_s \tag{24}$$

$$ss_{p,p+1,s} \in \{0,1\} \quad \forall s \in \{1,...,S\}, p \in Pat_s \tag{25}$$

$$ss_{0,P+1,s} \in \{0,1\} \quad \forall s \in \{1,...,S\} \tag{26}$$

$$sr_{p'po} \in \{0,1\} \quad \forall p' \in \{1,...,P\}, p \in \{1,...,P+1\}, p' \neq p, o \in \{1,...,O\} \tag{27}$$

$$ct_p \geq 0 \quad \forall p \in \{1,...,P\} \tag{28}$$

The objective functions summarized in objectives (1) and (2) involve reducing overhead costs and optimizing scheduled surgeries, which aligns with minimizing patient waiting time. Within this framework, the waiting period is treated uniformly, disregarding any distinctions between patients or their duration on the waiting list. Eq. (3) guarantees that each surgical procedure is scheduled exclusively when the surgeon is accessible on that day. Eq. (4) ensures that every surgery is allocated to a suitable slot based on its fit. Eq. (5) guarantees that the total scheduled surgical hours for each surgeon remain below the predetermined maximum limit. Eq. (6) and Eq. (7) require the inclusion of an alternative surgeon in the sequence of planned surgeries for each incumbent surgeon, both before and after every surgery. Eq. (8) and Eq. (9) also cause surgery to be placed at the beginning and end of each surgeon's sequence Unless no surgery is scheduled. Eqs. (10)–(13) have a similar function for the sequence of surgeries in the operations. Inequalities (14)–(17) determine the completion time of planned surgeries, which must be at least equal to the total duration of operation and recovery after the previous patient in the sequence of the surgeon and the duration of the operation after the previous patient in the sequence of the operating room. In these relations, *M* is a large number. A set of limitations are written for calculating idle and overtime times. Regarding Eq. (15), the patient's hypothetical surgery completion time is assumed to be zero to maintain consistency and avoid interfering with other computations. With the explanations provided earlier, Eqs. (20)–(28) appear straightforward when defining the nature of decision variables.

3. Solution Approaches

3.1. Simulation-based Optimization Technique

Operating room scheduling indeed faces various complications, including the variability in procedure durations such as surgery and recovery times. For instance, in the specific hospital under study, surgeries performed by the 18th surgeon specializing in pediatric heart procedures typically last between 5 to 8 hours. However, the method outlined in the previous section assumes a fixed surgery time of approximately 4 hours for patients under this surgeon's care. To address this complexity, simulation-based optimization techniques can be employed. These methods utilize simulations to account for the variability in procedure durations and other pertinent factors. By incorporating such variability into the optimization process, more realistic and robust scheduling decisions can be made, leading to improved operational efficiency and better patient outcomes. In simulation-based optimization, two primary components are involved: the optimizer and the simulator. The optimizer, often implemented as a meta-engineering method, generates various scenarios or solutions denoted as x. On the other hand, the simulator element computes the objective functions for each scenario x, providing an evaluation of the performance of each solution within the simulated environment by Figure 2. This iterative process allows for exploring different solution possibilities and their corresponding outcomes, ultimately aiding in selecting the most optimal solution. In this study, the optimizer and simulator elements are coded to interact easily with each other. This round-trip process continues until the optimizer stops.

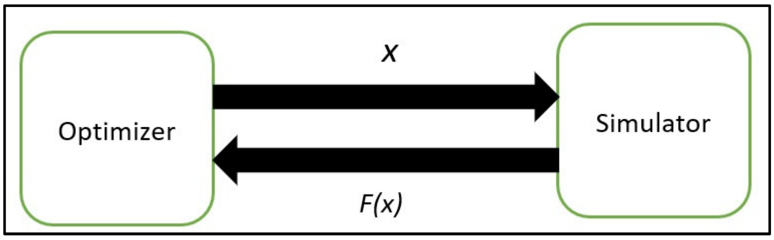

Fig. 2. The framework concept of simulation-based optimization.

The multi-objective evolutionary algorithm (MOEA) and non-dominated sorting genetic algorithm II (NSGA-II) methods were employed as part of the evolutionary multi-objective optimization techniques for the optimizer element. In this method, having prior knowledge of the relationship between the objective functions is crucial to derive a set of meaningful solutions. Given the absence of detailed information regarding the interplay between the two defined objective functions (cost and waiting time), these methods prove to be suitable options for tackling the scheduling challenges in operating rooms. Their ability to explore a diverse range of solutions without presuming a specific relationship between objectives makes them well-suited for such complex optimization problems. On the other hand, considering the nature of meta-innovation, these methods can help us obtain appropriate answers reasonably. In addition, it is possible to use them alongside simulation.

The NSGA-II algorithm operates as a multi-objective method, drawing from the principles of single-objective genetic algorithms. However, unlike in single-objective mode, where sorting the set of solutions involves straightforward comparison based on a single objective function value, multi-objective mode presents a challenge. Here, solutions cannot be simply compared by a single number; instead, the vectors of objective functions associated with each solution must be compared. This necessitates a more nuanced approach to sorting, as the algorithm seeks to balance solutions that offer improvements across multiple objectives rather than optimizing a single objective alone. In NSGA-II, various answers are sorted according to two ranking criteria - determined by the rule of dominance of the answers - and the crowding distance of the answers. More explanations about these two criteria are given in the article. The MOEA method used in this research has a similar function, with the difference that the number of answers and the number of children is determined in each stage according to the number of insignificant answers.

3.2. Matching Mathematical Model with Simulation

With the explanations given in the previous sections, if the duration of surgery and recovery of patients in the designed operating room simulator element is considered definite, the simulator should calculate the objective functions similar to the mathematical model. Five scenarios were defined to ensure this issue, and the objective functions were calculated using the mathematical model and simulator. As Table 2 shows, in all these scenarios, these two approaches estimate the value of the objective functions in the same.

Table 2
The scenario used for the mathematical model with the simulated system

Scenarios	Scenario features		Response	Objective function's quality	
	No. operating room	No. of patients		Mathematic model	Simulation model
1	10	42	No Surgery	(30,350)	(30,350)
2	8	30	unjustified	unjustified	unjustified
3	5	50	unjustified	unjustified	unjustified
4	5	20	justified	(20,40)	(20,40)
5	3	40	justified	(25,95)	(25,95)

Now, we have examined the model's performance under five distinct scenarios:

i. *Scenario 1* – Resources operate according to a continuous work schedule, including weekends, from 8:00 to 17:00, with no intervals of unavailability.
ii. *Scenario 2* – Resources adhere to a work schedule, including weekends, from 8:00 to 17:00, with no periods of unavailability. Patients arrive in batches at 8:00 a.m. each day throughout the planning horizon.
iii. *Scenario 3* – Resources adhere to a predefined work schedule, and each resource has designated periods of unavailability, as outlined in Table 2. Additionally, all resources take a one-hour break at noon. The quality objective function determines the duration of procedures.
iv. *Scenario 4* – Resources adhere to a work schedule with designated intervals of unavailability outlined in Table 2. Moreover, all resources incorporate a one-hour break at midday. Each patient is linked to a probability of not attending, which, interestingly, is randomly selected from a spectrum ranging between 0.5 and 1, adding a touch of unpredictability to the scheduling process.
v. *Scenario 5* – Table 2 indicates that resources operate based on a predetermined timetable, and every resource has a specific period when it is unavailable. All resources observe a one-hour halt at midday. Patients arrive in groups at the clinic at 8:00 every day.

Significant insights can be gained by comparing the two methods of addressing the workshop work scheduling problem specifically, the exact solution derived from the mathematical model and the optimization approach based on simulation. Despite its precision in finding the optimal solution, it becomes evident that the mathematical model may need to be more efficient in handling large and complex problems. Conversely, simulation-based optimization, leveraging the adaptability of meta-heuristic and simulation algorithms, offers viable solutions for large and intricate problems due to its flexibility. In a particular study, the exact solution of the mathematical model and simulation-based optimization were compared to solve the workshop work scheduling problem, which is comparatively simpler than our research problem. As mentioned earlier, when considering the likelihood of undergoing surgery and the duration of recuperation, the simulated component offers an equivalent depiction of the mathematical model of the issue. Furthermore, simulation offers a more precise depiction of the operating room by considering the intricacy of the system (including the likely duration of the processes). Consequently, the accuracy of the goal functions is enhanced when the mathematical framework solutions are evaluated using a simulator that performs a significant number of iterations.

4. Solution Approaches

The aim of this study is to develop a structured patient schedule that minimizes deviations from patients' desired start times and reduces overall patient flow time within the system. Performance evaluation is based on calculating the average flow time and total deviations from desired start times. In all scenarios, if a patient arrives at each stage before the end of the work shift, service by the resource will commence and continue until completion, even if it exceeds the resource's work shift. Based on the data gathered from the investigated hospital for this study, 15 sample problems were generated following the guidelines outlined in Table 3. We established four levels for the number of available operating rooms. Within each level, the rate of patients added to the waiting list for each type of surgeon determined the patient influx at intervals of one, two, and three days. Consequently, the sample problems consist of four operating room levels and three distinct patient levels.

Table 3
Comparison of the solution time of three methods in seconds

Test number	Number of operating rooms	Number of patients	Mathematical model	NSGA-II	MOEA
1		4	0.08	130	40
2	1	6	0.09	70	15
3		8	0.1	120	35
4		14	0.7	450	130
5	3	20	0.4	360	105
6		50	7800	680	350
7		18	0.3	340	100
8	5	36	8200	620	270
9		70	0.3	820	470
10		33	4	660	185
11	8	76	8100	800	300
12		117	0.02	2000	900
13		40	1.4	730	220
14	10	85	3.6	900	360
15		121	120	1900	1000

We coded the mathematical model and optimization method based on simulation with NSGA-II and MOEA algorithms in MATLAB R2014b software and implemented it using a computer with the following specifications. Considering the dual objective problem, we solved the mathematical model once with the first and second objective functions. Then, if the algorithm for solving the mathematical model reached a reasonable solution in less than an hour, we solved the third problem using the following objective function:

$$min \left[\frac{1}{case_1} \times \sum_{o=1}^{O} (T_o tar_o + I_o idl_o) - \frac{1}{case_2} \times \sum_{p=1}^{P} \sum_{o=1}^{O} x_{po} \right] \tag{29}$$

In relation case, it shows the interval of the first objective function, and case shows the interval of the second objective function in a colon, obtained by solving two problems (one considering the first objective function and the other with the second objective function). After solving the sample problems using all three methods, the answers were evaluated using simulation with 1000 repetitions. The solution time and the quality of the non-existent answers obtained from the three methods can be seen in Table 3 and Table 4, respectively.

Table 4
Comparing the quality of Pareto solutions obtained from three methods

Sample problem	Mathematical model	NSGA-II	MOEA
1	(20,2)	(20,2)	(20,2)
2	(30,5)	(30,5)	(30,5)
3	(22,5)	(22,5)	(22,5)
4	(50,4)	(50,4)	(50,4)
5	(75,15)	(70,15)	(70,15)
6	(80,30)(30,35)(20,35)	(20,34)(22,35)(18,40)	(30,35)(25,40)
7	(160,10)	(160,10)	(160,10)
8	(180,25)(20,110)(100,25)	(25,115)(25,100)(28,120)	(25,100)(25,110)
9	(70,200)	(50,60)(55,60)(55,54)	(50,65)(50,60)(50,58)
10	(20,250)	(20,250)	(20,250)
11	(40,65)	(55,200)(55,206)(57,190)	(56,195)(56,200)
12	(55,76)	(88,75)(75,85)(84,80)	(100,81)(97,77)(83,89)
13	(40,87)	(55,200)(55,206)(43,190)	(56,195)(56,200)
14	(76,65)	(95,200)(56,206)(52,192)	(56,75)(77,213)
15	(87,95)	(51,220)(55,206)(76,190)	(86,143)(56,200)

Additionally, the planning horizon duration aligns with the operational days of the clinic for patient service. Additionally, the cost ratio (*CR*) is derived by dividing the cost coefficient of total deviations from patients' preferred start days (α) by the cost coefficient of average patient flow time (β). For each scenario, we implement a meticulous beginning timetable, assuming that all patients will attend on their desired day of commencement. The planning horizon, set at one week, is a testament to our thoroughness. We also operate under the assumption of offline scheduling, a method that ensures we have comprehensive prior knowledge of our patient's information, such as their start day.

Figure 3 illustrates the variation in departure from the initial day across different scenarios as the cost ratio (CR) varies from 1 to 0.05. A CR value of 1 prioritizes scheduling patients close to their preferred start day, while a CR of 0.05 indicates that shorter patient flow time is significantly more important than scheduling patients on their preferred start day. In scenario 1, even with a reduced CR of 0.05, there is no substantial increase in the deviation from the start day. This observation suggests that altering patient start days may not necessarily reduce their average flow time when resource availability is unconstrained.

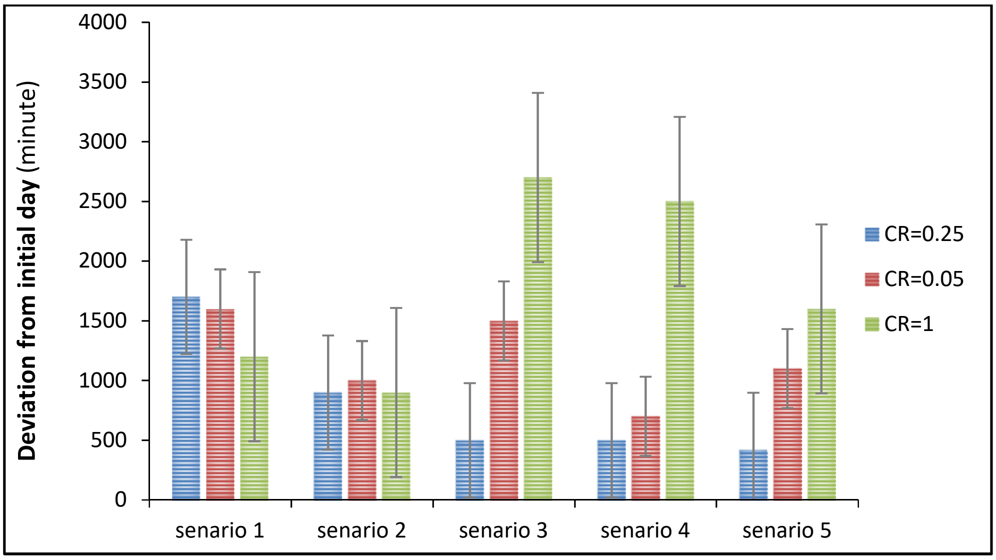

Fig. 3. Impact of cost ratio due to deviation from patient's preferred start day in various scenarios.

For example, Figure 4 shows the answers obtained from the three methods for sample problem 10. The vertical axis in this diagram shows the number of patients who could not be operated on the scheduled day, and the horizontal axis shows the overhead cost function. Considering that the surgeons of some waiting patients are absent on the scheduled day, it is natural that many patients still need to undergo surgery. For this reason, in the best answer regarding the patient's expectation function, 22 patients were not operated. Apart from this issue, although the dimensions of this problem are smaller (5 rooms and 36 patients), optimization methods based on simulation generally perform better for this problem and have produced more unique answers in less time. As can be seen in Tables 4 and 5, optimization methods based on simulation can generally solve large problems in a reasonable time. In addition to producing solutions with a quality close to the mathematical model in small problems, they can also produce solutions with a quality close to the mathematical model.

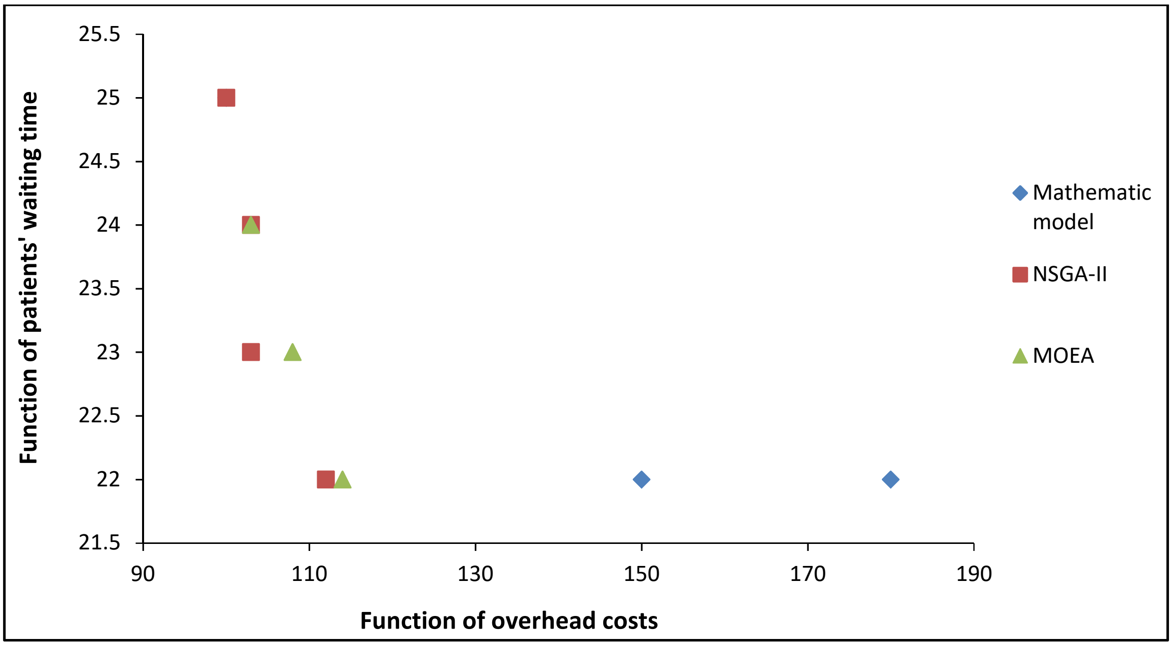

Fig. 4. The status of the answers obtained for the sample problem.

Furthermore, in Table 4, one of the solutions identified as inferior by the optimization based on simulation using MOEA is deemed superior in simulation with 1000 repetitions. This discrepancy can be attributed to the inherent randomness involved in the simulation process. In this study, efforts were made to mitigate the impact of this factor on the final evaluation of solutions by increasing the number of repetitions. Consequently, while this discrepancy is not trivial, it underscores the importance of considering the stochastic nature of simulation-based optimization. However, given the critical importance of time in evaluating solutions within simulation-based optimization, the number of repetitions needed to be increased. Therefore, it is unsurprising that a superior solution may occasionally be incorrectly identified as inferior due to random evaluation.

5. Discussion

Evaluate the effectiveness of the simulation-based optimization model in managing the scheduling of operating room (OR) operations within the restrictions of restricted capacity. Examine the duration, computing resources, and overall efficiency of generating schedules in comparison to alternative methods like manual scheduling or heuristic-based techniques. Evaluate the cost-effectiveness of adopting the simulation-based optimization model in comparison to other methods.

Assess the cost-benefit ratio by considering the starting costs, continuing maintenance charges, and the possible financial gains resulting from enhanced operational efficiency and patient outcomes. The study may need to examine the ethical implications of resource allocation decisions made through the simulation, which are essential to managing operating rooms in real-life situations.

6. Conclusion and Future Directions

The emergency department plays a crucial role within hospitals, engaging with numerous patients daily and facilitating various interactions among patients, staff, and resources. Its operational effectiveness and performance hinge on factors such as the quantity and allocation of doctors, nurses, beds, and other resources within the hospital. Considering the importance of reducing patients' waiting time and hospital costs, these two were considered the problem's objective functions. Then, to better understand the problem in a real hospital and evaluate the efficiency of mathematical modeling, the mathematical model of this problem was introduced. After that, the simulation-based optimization tool was built using two multi-objective evolutionary optimization methods, NSGA-II and MOEA algorithms. The only difference between the mathematical model and simulation-based optimization in the description of the operating room was the duration of the processes, which was considered a possibility in the simulation-based optimization. After ensuring the similar performance of the tools in the conditions where the duration of the processes was definite, their comparison was made.

The findings were achieved under the condition that, in this study, only one aspect of the fundamental operating room was simulated compared to the mathematical model. While it is feasible to incorporate additional complexities from the operating room into the simulation without greatly diminishing its effectiveness, integrating these complexities into the mathematical model can only be done at the cost of slowing it down. A potential future recommendation could involve expanding our methodology to include the concept of the stay bed as a communal resource that multiple wards can utilize. Another potential avenue for research could involve integrating resource scheduling with simulated annealing. This could include developing an artificial intelligence machine learning system to assess the effectiveness of emergency departments under varying levels of staffing, using data from multiple simulation outputs.

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