Original Research

Robust Scheduling and Planning of Operating Rooms and Sterilization Unit with Emergency and Elective Patients: Two Metaheuristic Algorithms

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Abstract

Great attention should be paid to planning and scheduling surgeries which is the most sensitive ward in the health context in terms of cost and specific sensitivity due to its association with the life and death of individuals. In this case, reusable sterile equipment and devices are crucial issues because the hospital or nosocomial infections result from insufficient sterilization of these instruments. Therefore, sterilization of reusable medical devices is a necessity in the operating room to prevent possible infections. This study solves the integrated operating rooms and sterile section planning problem to minimize the total costs of sterilization, surgery delay, and performance. This study also minimizes the completion time of surgery considering nondeterministic operating times and emergency-elective patients. In the real world, surgery time may be nondeterministic based on the conditions of the patient, surgeon, equipment, and instruments; hence, it is valuable to find a robust solution for planning under such circumstances. After using a bi-objective model for this problem, an improved ε-constraint method was implied to solve problems with small dimensions, and two metaheuristics NRGA and NSGA-II were developed for large dimensions regarding NP-hard problems. These two algorithms were analysed based on five indicators. The obtained results showed the superiority of the NSGA-II algorithm over NRGA to solve such problems.

Keywords- Operating and Sterile Rooms; Scheduling and Planning; Emergency and Elective Patients; Robust Optimization; Metaheuristic algorithms.

INTRODUCTION

Scheduling and planning surgeries in operating rooms are critical fields in the health system that should receive great attention since the life of people would be in danger if there is any improper planning and a minor postponement or delay. On the other hand, insufficient sterilization of reusable medical devices in the surgery ward is a reason for hospital infections. Hence, the surgery room must be cleaned and reusable devices and equipment must be sterilized at the end of surgery and before starting a new surgery. However, 70% of hospital clients need surgery and more than 15% of time waste in hospitals occurs in operating rooms [1]. Hence, many researchers have examined hospital planning, particularly surgery room scheduling and planning, by consideration of elective or nonelective (emergency) patients. It is worth noting that elective patients are those patients whose surgeries are planned, and nonelective or emergency patients should be operated on as soon as possible. Many studies have been conducted on elective patients. Belkhamsa et al. [2] used two metaheuristic iterative local search and hybrid genetic algorithm approaches to solve operating room scheduling problems. Maghzi et al. [3] used GAMS software and a random data set to solve operating room and hospital ward planning and scheduling to minimize patients' attendance time in the hospital. Kayvanfar et al. [4] used the Lagrange liberalization approach to solve the MIP model for operating room scheduling and recovery ward considering elective patients.

Another category of papers has examined emergency patients that need emergency and prompt services. For instance, Ali et al. [5] used MILP to solve surgery room scheduling for elective and emergency patients during the war. Kamran et al. [6] proposed two heuristic approaches for scheduling and planning patients sequence problems in operating rooms. Bovim et al. [7] used a simulation optimization model for scheduling elective and emergency surgeries. According to studies conducted by Spagnolo et al. [8], 38% of nosocomial infections are seen in surgical patients. Infection factors include insufficient sterilization of surgical wards or devices used in surgery that is required for preventing or reducing potential infections, and sterilization of reusable medical devices (RMD), such as a clamp, forceps, and endoscope. Hence, some studies have paid attention to sterilization wards in their studies. For example, Beroule et al. [9] solved operating room scheduling problems and medical device sterilization, by using a GA, PSO and TS. Ozturk et al. [10] used the MIP model and heuristic approach to minimize sterilization operation time in services for the sterilization of reusable medical devices. Moreover, Ozturk et al. [11] proposed a batch scheduling optimization model to reduce utilization and sterilization time using a MILP and dynamic programming, and an approximate algorithm.

The nature of operating room scheduling and programming faces uncertainty in the real world. Hence, some researchers have considered uncertainty in their studies. For example, Bruni et al. [12] solved the surgery room problem considering the uncertainty of surgery duration and emergency patients by using random programming modelling to maximize weekly revenue and minimize the expected overtime cost. Eun et al. [13] used sample mean approximation, local search, and tabu search approach to solve scheduling problems with random surgery duration of elective patients considering different disease severity and pointed to increased waiting time and worsen patient status. Kroer et al. [14] used two approaches to solve robust operating room scheduling and planning for elective and emergency surgeries to minimize overtime and release the idle capacity. M'Hallah and Visintin [15] considered a stochastic model with care unit times, uncertain surgery times, and the length of staying time after surgeries using a sample mean approximation method. Kamran et al. [16] used a heuristic method based on the column generation and Bender’s decomposition for scheduling comparative allocation of patients in operating rooms. They proposed a MILP model to minimize patients' cancellation, tardiness, operating room overtime, surgeons' idle, and surgery starting time for the emergency patient. Rachuba and Werners [17] minimized waiting for time, staff overtime, and tardiness by using a robust multiple optimization approach. Liu et al. [18] examined surgery scheduling problems by consideration of medical devices and operating room preparation time. Aissaoui et al. [19] used MILP and simulation approaches to solve the integrated allocation scheduling and resource sequence problem in private healthcare centres. They conducted this study by using a robust optimization technique. Coban [20] designed a single-purpose model by using a heuristic approach and rule-of-thumb to minimize costs for elective patients when all parameters are deterministic.

Mazloumian et al. [21] used a robust optimization approach for multi-objective integrated surgery scheduling and allocation model. Harris and Claudio [22] had a literature review for scheduling operating rooms between 2015 to 2020. Wang et al. [23] used a hybrid algorithm for fuzzy surgical scheduling. Yu et al. [24] verified the schedulinf of surgeries for saving time and money. Ghasemi et al. [25] used constraint programming and TOPSIS for solving surgery room scheduling. Bargetto et al. [26] used an exact algorithm for surgery room scheduling. Recently, Arjmandi and Samouei [27] considered robust scheduling and planning of sterile unit and surgery rooms for reusable surgical items. But they only used epsilon-constraint method, and they did not present any heuristic or metaheuristic for their problem. Since, decision-making in hospital, especially for surgeries and operating rooms which saving time is necessary and valuable, we present two metaheuristic algorithms for the problem. This study examines the total costs of emergency and elective operations, tardiness cost in surgery for elective patients, and maximum waiting time for emergency patients.

In addition, this paper minimizes the completion time of surgeries regarding the limited available resources, such as operating rooms, number of available devices, etc. An augmented ε-constraint method is used to solve the proposed model, and two metaheuristic algorithms of NRGA NSGA-II and are investigated regarding the NP-hard problem to evaluate it in terms of different indicators. Furthermore, several statistical analyses are used to verify which algorithm is better. Table 1 reports the studies that have examined our research scope indicating initiative aspects of the extant study compared to other studies.

TABLE 1
THE RELATED PAPERS OF THIS STUDY

Authors	Year	Type of Patient	Scheduling and planning		Uncertainty		Type of uncertainty	Number of objective functions		Solving method
			Operating room	Sterilization unit	Yes	No		Single	Multi	
Kayvanfar et al. [4]	2021	Elective	*			*			*	Lagrange relaxation
Ali et al. [5]	2019	Emergency and Elective	*			*			*	MILP
Bovim et al. [7]	2020	Emergency and Elective	*		*		Stochastic		*	Simulation and stochastic programming
Ozturk et al. [10]	2010	Elective		*		*		*		Heuristic method
Xu & Wang [28]	2018	Elective		*		*		*		GA
Kroer et al. [14]	2019	Emergency and Elective	*		*		Stochastic	*		MIP
Rachuba & Werners [17]	2015	Emergency and Elective	*		*		Robust		*	robust optimization
Liu et al. [18]	2017	Elective	*		*		Robust	*		Simulation and robust optimization
Coban [20]	2020	Elective	*	*		*		*		Heuristic method
Mazloumian et al. [21]	2022	Elective	*		*		Robust		*	robust optimization
Wang et al. [23]	2022	Elective	*		*		Fuzzy	*		a hybrid algorithm
Yu et al. [24]	2022	Elective	*			*			*	ICA and VNS
Ghasemi et al. [25]	2023	Elective	*			*			*	TOPSIS and constraint programming
Bargetto et al. [26]	2023	Emergency and Elective	*			*		*		A branch & price& cut algorithm
This paper	2023	Emergency and Elective	*	*	*		Robust		*	Robust optimization, NSGA-II and NRGA

LITERATURE REVIREW

Each operating rooms is the vital resource in hospital that provides services while incurring high costs. Hence, scheduling and planning are required to costs reduction and improve the services quality. Furthermore, medical devices are vital resources used in surgery, and any shortage in this field may result in surgery tardiness, which may put the life of emergency patients at risk of death. Medical devices are sterilized which classified as single-use and reusable medical devices (RMD). Single-use items, such as needles, are disposed of after being used for one patient's surgery. Reusable medical devices, such as clamps, forceps, and endoscopes are sterilized and disinfected fully then reused. Therefore, RMD planning is highly crucial.

The present paper considers elective and emergency operations in which emergency patients should undergo surgery as soon as possible. The number and time of considered emergency patients have been planned based on the model proposed by Kroer et al. [14]. A cost has been considered for elective and emergency operations; in this case, the cost of surgery for emergency patients is less than it is for elective surgeries to prioritize emergency patients. Furthermore, a maximum waiting time is considered for each emergency patient. Operation is not started before the arrival of emergency patients, and they should not wait more than the maximum waiting time. Those surgeries are impossible to do during working hours are postponed or traded. The minimum number of reusable medical devices is kept sterilized in each period. The number of RMDs differs for each patient based on their physical condition. The sterilization length of RMD is predetermined. On the other hand, the number of sterilizing devices must not exceed the number of sterile devices. A certain capacity of each sterile device must be considered. Surgery length has uncertainty regarding the conditions of patients, surgeons, and devices. Hence, a robust approach was proposed to overcome this uncertainty. Moreover, two objectives were considered in this problem: minimizing the total cost of using sterilization devices, the penalty paid for tardiness in elective patients' surgery and operation cost, and minimizing the last surgery completion time in operating rooms to release rooms for the next operations.

MODELLING AND PRESENTING SOLUTION METHODS

The extant study used a model to minimize total costs and completion time of the last surgery for scheduling and planning the operating rooms considering the elective and emergency patients in two deterministic and robust modes. These models are presents in Arjmandi and Samouei [27]. For this purpose, assumptions, indexes, parameters, sets, and decision variables of these two models are introduced herein:

I Model's Assumptions

- Elective and emergency patients are considered.
- Emergency patients cannot wait for more than the reasonable waiting time due to their conditions.
- Several operating rooms exist that are suitable for all surgeries.
- The required manpower is not a constraint during the planning period
- Planning horizon length is periodic considering 15-min duration.

II. Indexes, Parameters, Sets, ad Decision Variables

Indexes

i, j: surgeries i, j∈I
a: emergency surgeries a∈A
b: elective surgeries b∈B
t: period t∈T
r: operating rooms r∈R

Sets

A: Emergency surgeries
B: Elective surgeries
I: Operations I=A∪B
T: Times
R: Operating rooms

Parameters

h_0= number of clean RMDs in time 0
d_0= number of dirty RMDs in time 0
M: a very large positive number
T': planning horizon length
n_i= number of RMDs required for surgery i
p_i= length of surgery i
ster: Sterilization required time
cap: capacity of each sterile device
mach: number of sterile devices
cost1: cost of using sterile devices
$cost2_b$: cost of tardiness in elective surgery
$cost3_a$: cost of emergency surgeries that is lower than the surgery for elective patients to prioritize surgery for emergency patients
$cost4_b$: cost of elective surgeries
e_a: maximum waiting time for emergency patients a
v_a: arrival time of emergency patient a
buffer: minimum clean RMD required for each period

Decision Variables

$X_{i,t,r}$: 1 if surgery i is done in time t in surgery room r, 0 otherwise
$f_{i,j,r}$: 1 if the surgery i id done sooner than operation j in operating room r, 0 otherwise
h_t: number of clean RMDs at the beginning of period t
d_t: number of dirty RMDs at the beginning of period t
o_t: number of sterilized RMDs at the beginning of period t
m_t: number of sterile devices start sterilization at the beginning of period t

$t'_{i,r}$: start time of surgery i in operating room r
$c_{i,r}$: end time of surgery i in operating room r
C_{max}: completion time of last surgery

III. Mathematical Model with Deterministic Times

A mathematical model of the problem under certain or deterministic conditions is designed as follows:

$$\min \sum_{t\in T} cost_1 m_t + \sum_{b\in B}\sum_{t\in T}\sum_{r\in R} t\, cost_{2b}\, x_{b,t,r} + \sum_{a\in A}\sum_{t\in T}\sum_{r\in R} cost_{3a}\, x_{a,t,r} + \sum_{b\in B}\sum_{t\in T}\sum_{r\in R} cost_{4b}\, x_{b,t,r} \quad (1)$$

$$\min C_{max} \quad (2)$$

S.to:

$h_{t-1} - \sum_{r\in R}\sum_{a\in A} n_a\, x_{a,t,r} - \sum_{r\in R}\sum_{b\in B} n_b\, x_{b,t,r} + o_{t-ster} = h_t \qquad \forall\, t \in T, t \geq 1 + ster \qquad (3)$

$h_{t-1} - \sum_{r\in R}\sum_{a\in A} n_a\, x_{a,t,r} - \sum_{r\in R}\sum_{b\in B} n_b\, x_{b,t,r} = h_t \qquad \forall\, t \in T, t \leq ster \qquad (4)$

$d_{t-1} - o_t + \sum_{r\in R}\sum_{a\in A: t-p_a\geq 1} n_a\, x_{a,t,r} + \sum_{r\in R}\sum_{b\in B: t-p_b\geq 1} n_b\, x_{b,t,r} = d_t \qquad \forall\, t \in T \qquad (5)$

$o_t \leq cap\; m_t \qquad \forall\, t \in T \qquad (6)$

$m_t \leq mach \qquad \forall\, t \in T, t \geq 1 + ster \qquad (7)$

$\sum_{a\epsilon A} x_{a,t,r} + \sum_{b\epsilon B} x_{b,t,r} \leq 1 \qquad \forall\, t \in T, r \in R \qquad (8)$

$\sum_{t\epsilon T: t\leq T'-p_b} \sum_{r\epsilon R} x_{b,t,r} = 1 \qquad \forall b \in B \qquad (9)$

$\sum_{t=v_a}^{t=v_a+e_a} \sum_{r\epsilon R} x_{a,t,r} = 1 \qquad \forall a \in A \qquad (10)$

$h_t \geq buffer \qquad \forall\, t \in T \qquad (11)$

$t'_{a,r} \geq t\, x_{a,t,r} \qquad \forall a \in A, r \in R, t \in T, t \geq v_a, t \leq v_a + e_a \qquad (12)$

$t'_{b,r} \geq t\, x_{b,t,r} \qquad \forall b \in B, r \in R, t \in T \qquad (13)$

$C_{j,r} - C_{i,r} + M(1 - \sum_{t\epsilon T} x_{j,t,r}) + M(1 - \sum_{t\epsilon T} x_{i,t,r}) + M(1 - f_{i,j,r}) \geq p_j + ster \qquad \forall\, j \in I, i \in I, r \in R, i \neq j \qquad (14)$

$C_{i,r} - C_{j,r} + M(1 - \sum_{t\epsilon T} x_{i,t,r}) + M(1 - \sum_{t\epsilon T} x_{j,t,r}) + M(f_{i,j,r}) \geq p_i + ster \qquad \forall\, j \in I, i \in I, r \in R, i \neq j \qquad (15)$

$C_{i,r} = \sum_{t\epsilon T}(t + p_i)(x_{i,t,r}) \qquad \forall\, i \in I, r \in R \qquad (16)$

$Cmax \geq C_{i,r} \qquad \forall\, i \in I, r \in R \qquad (17)$

$x_{i,t,r} \in \{0,1\} \qquad \forall\, i \in I, t \in T, r \in R \qquad (18)$

$f_{i,j,r} \in \{0,1\} \qquad \forall\, i \in I, j \in I, r \in R \qquad (19)$

$h_t, d_t, o_t, m_t \geq 0 \;\text{ and integer} \qquad \forall\, t \in T \qquad (20)$

In the model, objective function (1) minimizes the total cost of sterilization, tardiness cost in elective operations, and the timely operation cost. Objective function (2) minimizes the last surgery completion time. Equations (3) and (4) point to the balanced inventory of sterilization devices regarding their sterilization times. The term (5) indicates the number of dirty (unsterilized) devices in each period. Constraint (6) points to the capacity of sterilization devices. Constraint (7) indicates the maximum number of sterilization devices. Constraint (8) explains that at most one surgery is done at each time and operating room. Constraints (9) and (10) denote the requirement for emergency and elective surgeries. Constraint (11) indicates the minimum number of sterilization devices in each period. Constraint (12) determines the start time of emergency surgery. Surgery does not begin before an emergency patient arrival, and the surgery must not be delayed more than the maximum reasonable time regarding the patient's condition. Constraint (13) determines the elective surgeries start time. Constraints (14) and (15) show the sequence and scheduling for two operations in one surgery room considering the length of surgeries and their sterilization times. Constraint (16) determined the completion time of surgeries. Constraint (17) determines the last surgery time. Constraints (18)-(20) indicate the variables' status.

IV. Robust Approach

This study considers surgery time an indeterministic parameter due to its inherent volatilities due to the specific conditions of each patient, the type of surgery, and the different experiences and skills of surgeons. This study used the Mulvey et al. [29] robust model to solve the problem under the considered conditions. Mulvey et al. [29] presented a framework for robust optimization, which include two concepts of “robust solution” and “robust model”. Accordingly, a solution is robust when all scenarios remain near to optimum point. Moreover, a model is robust when all scenarios are almost reasonable or justifiable. Penalty and weight are assigned to the lack of a model and solution robust in an objective model of [29]. An exchange occurs between model robustness and solution regarding the decision-maker's preferences in this model. Consider following the linear programming model with stochastic parameters for a better explanation:

$$\min c^T x + d^T y \quad (21)$$
$$\text{s.to: } Ax = b \quad (22)$$
$$Bx + Cy = e \quad (23)$$
$$x \geq 0, \quad y \geq 0 \quad (24)$$

Variable x denotes a vector of design variables and variable y represents the control variable. Matrixes A, B, and C include parameters of variables' coefficients at the left side of constraints; e and b denote the vector of right-hand parameters. Moreover, A and b are deterministic and B, C, and e are indeterministic. The actualization of each value for the indeterministic parameter is called a scenario, which is indicated by s and probability p_s. The set of scenarios is shown by Ω={1,2,…, S}. indeterministic coefficients B, C, and e are indicated as C_s, B_s, and e_s for each scenario. Moreover, the set $\{y_1, y_2, \ldots, y_s\}$ includes a set of control variables for each scenario. The model is formulated as follows:

$$\min \gamma(x, y_1, y_2, \ldots, y_s) + \omega p(\eta_1, \eta_2, \ldots, \eta_s) \quad (25)$$
$$\text{s.to: } Ax = b \quad (26)$$
$$B_s x + C_s y_s + \eta_s = e_s \qquad \forall s \in \Omega \quad (27)$$
$$x \geq 0, \quad y_s \geq 0, \quad \eta_s \geq 0 \qquad \forall s \in \Omega \quad (28)$$

The model might be unjustifiable for some scenarios due to indeterministic parameters. The set $\{\eta_1, \ldots, \eta_s\}$ includes error vectors measuring the unjustifiableness rate of each scenario. The η_s equals 0 id model is reasonable for scenario s, it will be a positive number otherwise. In this model, the robustness part of the solution in the objective function has γ weight, and model robustness takes the weight ω. In the first part, solution robustness is considered, and ξ_s indicated the cost function or $f(x, y_s)$. Mulvey et al. [29] used the following equation for this part:

$$\sigma(0) = \sum_{s\in\Omega} p_s \xi_s + \gamma \sum_{s\in\Omega} p_s \left|\xi_s - \sum_{s'\in\Omega} p_{s'} \xi_{s'}\right| \quad (29)$$

The problem can be converted to the following linear form:

$$\text{Min } \sum_{s\in\Omega} p_s \xi_s + \gamma \sum_{s\in\Omega} p_s \left[\left(\xi_s - \sum_{s'\in\Omega} p_{s'} \xi_{s'}\right) + 2\theta_s\right] \quad (30)$$
$$\text{s.to: } \xi_s - \sum_{s\in\Omega} p_{s'} \xi_{s'} + \theta_s \geq 0 \qquad \forall s \in \Omega \quad (31)$$
$$\theta_s \geq 0 \qquad \forall s \in \Omega \quad (32)$$

The stochastic robust programming model can be formulated after inserting a penalty for model unjustifiability:

$$\min \sum_{s\in\Omega} p_s \xi_s + \gamma \sum_{s\in\Omega} p_s \left[\left(\xi_s - \sum_{s\in\Omega} p_{s'} \xi_{s'}\right) + 2\theta_s\right] + \omega \sum_{s\in\Omega} p_s \eta_s \quad (33)$$
$$\text{s.to: } Ax = b \quad (34)$$
$$B_s x + C_s y_s + \eta_s = e_s \qquad \forall s \in \Omega \quad (35)$$
$$\xi_s - \sum_{s\in\Omega} p_{s'} \xi_{s'} + \theta_s \geq 0 \qquad \forall s \in \Omega \quad (36)$$
$$\theta_s \geq 0, \quad x \geq 0, \quad y_s \geq 0, \quad \eta_s \geq 0 \qquad \forall s \in \Omega \quad (37)$$

V. Robust Mathematical Model with Indeterministic Times

This part of the study uses the robust model of a problem for operating room and sterilization planning with indeterministic times which it is presented in [27]. It is worth noting that the following elements are used in addition to the variables, indexes, and sets introduced above:

Indexes

s, s': scenarios $s, s' \in \Omega$

Sets

Ω: the set of scenarios

Parameters

p_i^s: Length of surgery *i* under the scenario *s*
π^s: Scenario *s* probability
λ: weight of solution robust variability
ω: unjustifiability weight of model robustness

Decision Variables

δ_i^s: unjustifiableness rate of a model comprising unmet demand for surgery i in scenario s

$c_{i,r}^{s}$: completion time of surgery i under scenario s
$C_{max}{}^{s}$: The last surgery completion time under scenario s

$$\min \sum_{t\in T} cost_1 m_t + \sum_{b\in B}\sum_{t\in T}\sum_{r\in R} t\, cost_{2b}\, x_{b,t,r} + \sum_{a\in A}\sum_{t\in T}\sum_{r\in R} cost_{3a}\, x_{a,t,r} + \sum_{b\in B}\sum_{t\in T}\sum_{r\in R} cost_{4b}\, x_{b,t,r} \tag{38}$$

$$\min\ \lambda \sum_{s\in\Omega} \pi^s c_{max}{}^{s} + (1-\lambda)\sum_{s\in\Omega}\pi^s\left[\left(c_{max}{}^{s} - \sum_{s'\in\Omega}\pi^{s'} c_{max}{}^{s'}\right) + 2\theta^s\right] + \omega\sum_{s\in\Omega}\sum_{i\in I}\pi^s\,\delta_i^s \tag{39}$$

S.to:

$$h_{t-1} - \sum_{r\in R}\sum_{a\in A} n_a\, x_{a,t,r} - \sum_{r\in R}\sum_{b\in B} n_b\, x_{b,t,r} + o_{t-ster} = h_t \qquad \forall\, t\in T, t\geq 1+ster \tag{40}$$

$$h_{t-1} - \sum_{r\in R}\sum_{a\in A} n_a\, x_{a,t,r} - \sum_{r\in R}\sum_{b\in B} n_b\, x_{b,t,r} = h_t \qquad \forall\, t\in T, t\leq ster \tag{41}$$

$$d_{t-1} - o_t + \sum_{r\in R}\sum_{a\in A: t-p_a^s\geq 1} n_a x_{a,t,r} + \sum_{r\in R}\sum_{b\in B: t-p_b^s\geq 1} n_b\, x_{b,t,r} = d_t \qquad \forall\, t\in T, s\in\Omega \tag{42}$$

$$o_t \leq cap\ m_t \qquad \forall\, t\in T \tag{43}$$

$$m_t \leq mach \qquad \forall\, t\in T, t\geq 1+ster \tag{44}$$

$$\sum_{a\epsilon A} x_{a,t,r} + \sum_{b\epsilon B} x_{b,t,r} \leq 1 \qquad \forall\, t\in T, r\in R \tag{45}$$

$$\sum_{t\epsilon T: t\leq T'-p_b^s}\sum_{r\epsilon R} x_{b,t,r} = 1 \qquad \forall b\in B, s\in\Omega \tag{46}$$

$$\sum_{t=v_a}^{t=v_a+e_a}\sum_{r\epsilon R} x_{a,t,r} = 1 \qquad \forall a\in A \tag{47}$$

$$h_t \geq buffer \qquad \forall\, t\in T \tag{48}$$

$$t'_{a,r} \geq t\, x_{a,t,r} \qquad \forall a\in A, r\in R, t\in T, t\geq v_a, t\leq v_a+e_a \tag{49}$$

$$t'_{b,r} \geq t\, x_{b,t,r} \qquad \forall b\in B, r\in R, t\in T \tag{50}$$

$$C_{j,r}^{s'} - C_{i,r}^{s} + M\left(1-\sum_{t\epsilon T} x_{j,t,r}\right) + M\left(1-\sum_{t\epsilon T} x_{i,t,r}\right) + M\left(1-f_{i,j,r}\right) \geq p_j^{s'} + ster \qquad \forall\, j\in I, i\in I, r\in R, i\neq j, s, s'\in\Omega \tag{51}$$

$$C_{i,r}^{s} - C_{j,r}^{s'} + M\left(1-\sum_{t\epsilon T} x_{i,t,r}\right) + M\left(1-\sum_{t\epsilon T} x_{j,t,r}\right) + M\left(f_{i,j,r}\right) \geq p_i^{s} + ster \qquad \forall\, j\in I, i\in I, r\in R, i\neq j, s, s'\in\Omega \tag{52}$$

$$C_{i,r}^{s} = \sum_{t\epsilon T}(t+p_i^s)\left(x_{i,t,r}\right) + \delta_i^s \qquad \forall\, i\in I,\ r\in R, s\in\Omega \tag{53}$$

$$c_{max}{}^{s} \geq C_{i,r}^{s} \qquad \forall\, i\in I,\ r\in R,\ s\in\Omega \tag{54}$$

$$\left(c_{max}{}^{s} - \sum_{s'\epsilon\Omega}\pi^{s'} c_{max}{}^{s'}\right) + \theta^s \geq 0 \qquad \forall s\in\Omega \tag{55}$$

$$x_{i,t,r}\in\{0,1\} \qquad \forall\, i\in I,\quad t\in T,\quad r\in R \tag{56}$$

$$f_{i,j,r}\in\{0,1\} \qquad \forall\, i\in I,\quad j\in I,\quad r\in R \tag{57}$$

$$h_t, d_t, o_t, m_t \geq 0 \ \text{ and integer} \qquad \forall\, t\in T \tag{58}$$

In this model, Equation (38) minimizes the total costs of sterilization, tardiness in elective surgeries, and cost of operations. Equation (39) minimizes the last surgery completion time. Equations (40) and (41) balance the number of sterilization devices regarding their sterilization time. The term (42) indicates the number of unsterilized devices in each period. The constraint (43) points to the capacity of sterilization devices. The constraint (44) denotes the maximum number of sterilization devices. The constraint (45) indicates one surgery is done in each operating room per time. Constraints (46) and (47) point to the requirement of elective and emergency surgeries for patients. The constraint (48) indicates the minimum number of sterilization devices in each period. The constraints (49) and (50) indicate start times of emergency and elective surgeries, respectively. The constraints (51) and (52) indicate simultaneous scheduling for two surgeries in one operating room regarding the surgeries' lengths and sterilization time. The constraint (53) indicates the surgeries completion time in each operating room under each scenario. The constraint (54) denotes the last surgery completion time under each scenario. The constraint (55) is the control constraint under each scenario. The other constraints indicate the variables' status.

VI.Augmented Epsilon Constraint

Different technics are used to solve multi-objective problems, including Epsilon Constraint Technic. In this technic an objective function is the main and the other objective functions are as the constraints. Augmented Epsilon Constraint is one of the developments of Epsilon Constraint. This method generates feasible solutions, and the solution algorithm is terminated and not solved for subsequent iterations if the problem is not feasible. Hence, Augmented Epsilon Constraint offers higher solution speed compared to conventional Epsilon Constraint. Moreover, unlike conventional epsilon constraint, the augmented version uses Lexicographic optimization to form a balance table and generate Pareto solutions, the extant study also uses this method to solve small and medium-scale problems through GAMS software. Because large-scale scheduling problems are NP-Hard, the large-scale problem designed in this study could not be solved within a reasonable time through GAMS software. Hence, this study uses two metaheuristic algorithms for solution and analysed the obtained results.

VII.NSGA-II

Deb et al. [30] introduced NSGA-II algorithm based on the elitism and crowding criterion for a fast and uncomplicated sorting phase. This algorithm is done as follows:

1. Initial population Creation
2. Calculating fit criteria
3. Population sorting based on the domination conditions
4. Measuring crowding distance
5. Selection
6. Creating mutation and crossover to generate new offspring
7. The initial population integration into the population created by mutation and crossover
8. The parent population replacing with the best members
9. Repeating the abovementioned steps until reaching the termination condition

NSGA-II algorithm is implemented for the introduced model as follows:

VIII.Solution Display

A structure must be used for solution display in all metaheuristic algorithms. This study uses a matrix to indicate surgery orders in each operating room per day. The number of cells of the proposed chromosome solution matrix equals a stochastic vector consisting of numbers 0 and 1 with an I+R-1 scale where I indicates the number of surgeries and R represents the number of surgery rooms. For instance, if it is required to schedule five surgeries in 2 operating rooms then we can have one stochastic chromosome with a length of 6, as shown in Figure 1.

0.619	0.332	0.982	0.248	0.081	0.43

FIGURE 1
CREATING IN STOCHASTIC CHROMOSOME WITH STOCHASTIC BINARY NUMBERS (BETWEEN 0 AND 1)

The matrix shown in Figure 1 is sorted ascending, and each element of the main vector is determined in the next step then the largest numbers are determined based on the number of operating rooms to use as a separator. Figure 2 is shaped in this step and then we begin from the left side of the vector to find the order and allocation of surgeries performed in each operating room. This Figure indicates that surgery 5 is done in the operating room then surgery 3 is performed. Moreover, surgeries 2, 1, and 4 are performed in the second operating room, respectively.

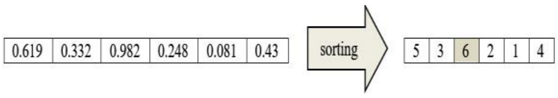

FIGURE 2
SORTING NUMBERS AND DETERMINING THE POSITION OF SEPARATORS IN THE SOLUTION DISPLAY

IX.Creating Initial Solution

The usual method for initial solutions creation in metaheuristic algorithms is generating a stochastic solution. In this study, we create stochastic numbers in size of chromosome length (I+R-1) for surgery assignment and scheduling.

X.Crossover Operator

This operator is the most important feature of the algorithm in which, two selected parents are combined to generate one or more offspring as a new solution. In this research, a two-point crossover operator is used. Figure 3 indicates a sample of a two-point crossover function.

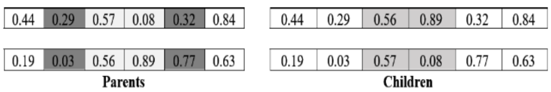

FIGURE 3
CROSSOVER FUNCTION

XI.Mutation Operator

This study randomly uses one of the swap, insertion, and reversion operators for mutation and creating a neighbourhood. The mentioned operators work as follows:

- ***Swap Operator***

This operator selects two stochastic points of chromosomes and swaps their place. Figure 4 indicates how this operator works.

0.619	0.332	0.982	0.248	0.081	0.43
0.619	0.081	0.982	0.248	0.332	0.43

FIGURE 4
SWAP OPERATOR EXAMPLE

- ***Insertion Operator***

This operator selects two stochastic points of chromosomes and then inserts the first point towards the right side of the second point. Figure 5 depicts an example of this operator.

0.619	0.332	0.982	0.248	0.081	0.43
0.619	0.982	0.248	0.081	0.332	0.43

FIGURE 5
INSERTION OPERATOR EXAMPLE

- ***Reversion Operator***

This operator selects two stochastic points of chromosomes and swaps two points the reverses values between these two points. Figure 6 indicates how this operator works.

0.619	0.332	0.982	0.248	0.081	0.43
0.619	0.081	0.248	0.982	0.332	0.43

FIGURE 6
REVERSION OPERATOR EXAMPLE

XII.Strategy for dealing with infeasible solutions

Each algorithm considers common strategies for infeasible solutions. This study uses the penalty function when there are infeasible solutions. For instance, a high penalty is added to objective functions in case of failure to perform surgery, long waiting time for the emergency patient, ignoring the maximum number of devices, or inaccessibility to required sterilization devices.

XIII.Sorting Population Members

Consider solutions x and y are the feasible or justifiable solutions in multi-objective functions; x dominates y if y is not better than x and x is strictly better than y in at least in one respect. Non-dominated solutions are called Pareto optimum solutions. After the initial population was sorted based on the dominance conditions in this algorithm, the crowding distance is measured and selection is done based on the two metrics of population rank and distance measurement. In population rank, populations with lower ranks are selected. In the distance measurement case, p and q are assumed as two members from the same rank, and the member with the longer crowding distance is chosen. Finally, population members are pairwise compared, and the population is sorted based on domination and crowding distance.

XIV.Algorithm Termination Condition

Various conditions can be chosen as termination criteria. This research uses the number of iterations for algorithm termination.

XV.NRGA

Al Jadaan et al. [31] developed an NRGA algorithm for discrete optimization, nonlinear, non-convex problems. The NRGA and NSGA-II are different in terms of selection and population sorting. In NRGA, ranked-based roulette wheel selection is used instead of a swarm race operator [32] so that better members are selected with a higher probability for reproduction and formation of the next generation. Each member has two features: the rank of the non-dominated border it is placed and the rank in the border based on the crowding distance.

XVI. Computational Analysis

The proposed model of this study was solved in small dimensions using the AEC method, while NRGA and NSGA-II algorithms were used for large dimensions. Moreover, the quality of metaheuristic algorithms' performance is highly affected by the values of their input parameters. Taguchi method was used to set parameters and for better application of the two mentioned algorithms. Moreover, various indicators and statistical assumption tests were used to evaluate the efficiency of the abovementioned algorithms.

XVII.Taguchi Method for Setting the Parameters

Taguchi introduced this method in 1986, and use signal-to-noise ratio which smaller values are better in minimization problems, and larger values are better in maximization problems [34].This study used four MaxIt, NPop, PC, and PM parameters for two NRGA and NSGA-II algorithms at three levels introduced in Table 2.

TABLE 2
THE LEVELS OF EACH PARAMETER OF THE BOTH ALGORITHMS

levels	NSGA-II			NRGA		
	1	2	3	1	2	3
Parameters						
Population (NPop)	20	60	100	20	60	100
Crossover Percentage (PC)	0.6	0.7	0.8	0.6	0.7	0.8
Percentage(PM) Mutation	0.1	0.2	0.3	0.1	0.2	0.3
Maximum iteration (MaxIt)	100	300	500	100	300	500

Nine tests were suggested by Minitab16 software using Taguchi method to determine the most efficient level of each parameter. To achieve higher performance precision, each test was implemented 25 times through MATLAB R2020b software. Finally, the mean value of four NPS, MID, SM, and DM indicators was used for multi-objective problems. After normalizing and considering positive and negative indicators, this study integrated them as [34]. The outcome was used as equation (59) to determine the response variable.

$$\text{Response} = \sqrt[2]{(\text{MID})^2 + (\text{SM})^2 + (\text{DM})^1 + (\text{NPS})^1} \tag{59}$$

The four indicators have been introduced herein:

Number of Pareto Solutions(NPS): This indicator shows the number of solutions existing in Pareto pertained. The greater value of this index is the best [35].

Mean Ideal Distance(MID): This index is used to find the distance between Pareto solutions and the ideal point of solutions [36]. In this case, n represents the number of Pareto points. Moreover, $f_{i,total}^{min}$ and $f_{i,total}^{max}$ represent minimum and maximum values of objective functions, respectively, and $f_1^{best}$and f_2^{best} indicate the ideal point's coordinates.

$$\text{MID}=\frac{\sum_{i=1}^{n}\sqrt{\left(\frac{f_{1i}-f_1^{best}}{f_{1,total}^{max}-f_{1,total}^{min}}\right)^2+\left(\frac{f_{2i}-f_2^{best}}{f_{2,total}^{max}-f_{2,total}^{min}}\right)^2}}{n} \tag{60}$$

Spacing Metric(SM): It measures the uniformity of a set of non-dominated points in solution space based on Equation (61) where n indicated many Pareto solutions, is the Euclidean distance between two Pareto solutions is shown with d_i , and the average distances between d_i values is $\bar{d}$ [30].

$$\text{SM}=\frac{\sqrt{\frac{\sum_{i=1}^{n}(d_i-\bar{d})^2}{n}}}{\bar{d}} \tag{61}$$

Diversification Metric(DM): It shows the Pareto solution diversity based on Equation (62) where f_m^j and f_m^i indicate the objective function m[th] values for two Pareto solutions i and j.

$$d_i = maxj\left\{\sum_{m=1}^{M}\left(f_m^i - f_m^j\right)^2\right\} \tag{62}$$

$$\text{DM}=\sqrt{\sum_{i=1}^{N} d_i}$$

Table 3 reports the normalized values and response variables. It is worth noting that all results are obtained from a system with Intel(R) Core (TM) i5- 4200U, 8GB memory, and Windows 10.

TABLE 3
THE NORMALIZED AND MEASURING RESULTS FOR SETTING PARAMETERS OF THE BOTH ALGORITHMS

Test	Parameter				NSGA-II					NRGA				
					Indexes				Response	Indexes				Response
	NPop	Pc	Pm	MaxIt	NPS	DM	SM	MID		NPS	DM	SM	MID	
L1	1	1	1	1	0.667	1	0.635	0.934	1.715	0.25	0.266	0.811	0.653	1.265
L2	1	2	2	2	0	0.311	1	0.722	1.354	1	0.707	0.022	0.889	1.58
L3	1	3	3	3	0.833	0.795	0.049	0.899	1.561	0	0.151	0.661	0.592	0.969
L4	2	1	2	3	0.75	0.395	0.077	0.627	1.243	0.5	0.320	0	0.766	1.186
L5	2	2	3	1	0.833	0.692	0.266	0.896	1.549	0.75	0.0501	0.544	0.617	1.388
L6	2	3	1	2	0	0	0.36	0.470	0.593	1	0.393	0.638	0.733	1.527
L7	3	1	3	2	0.333	0.667	0.971	0.669	1.546	0.5	0	0.829	0.260	1.120
L8	3	2	1	3	0.75	0.295	0	0	1.022	0.5	0.151	1	0	1.286
L9	3	3	2	1	1	0.841	0.029	1	1.686	0.75	1	0.569	1	1.753

Now, the S/N ratio is measured based on response values. The level of each parameter is determined based on Figures 7 and 8.

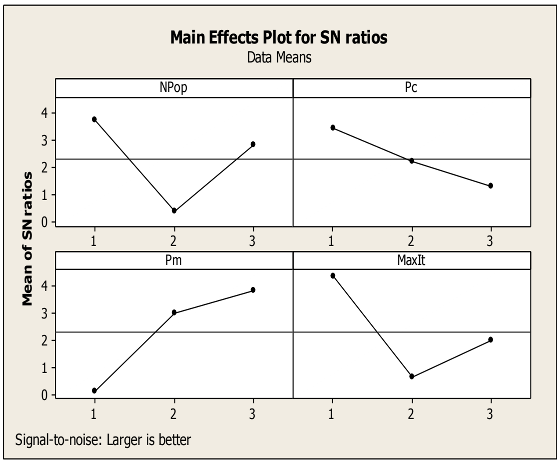

FIGURE 7
S/N RATIO FOR NSGA-II ALGORITHM

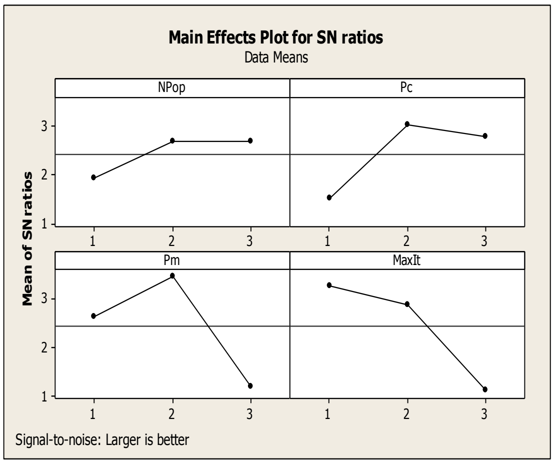

FIGURE 8
S/N RATIO FOR NRGA ALGORITHM

Hence, the final result of setting parameters is reported in the Figures shown in Table 4. As it is seen, two considered algorithms have different values despite identical parameters being considered to set parameters for these two algorithms.

TABLE 4
THE FINAL RESULT OF THE SETTING PARAMETER

Parameter	NPop	PC	PM	MaxIt
NSGA-II	20	0.6	0.3	100
NRGA	100	0.7	0.2	100

Several problems were created randomly to compare algorithms and results of model solutions based on the AEC method. Table 5 reports the comparative results. As can be seen, solution time is highly increased from a certain dimension threshold. Metaheuristic algorithms are required regarding the nature of the problem and instant response to patients.

TABLE 5
COMPARING THE RESULTS OF NSGA-II, NRGA, AND AEC ALGORITHMS FOR SEVERAL EXAMPLES

Dimension	AEC [27]			NSGA-II			NRGA		
i*r*t	The first objective function	The second objective function	Solution time (sec)	The first objective function	The second objective function	Solution time (sec)	The first objective function	The second objective function	Solution time (sec)
4*3*20	1250	6.60	12.29	1550	14	5.25	1550	14	72.83
5*4*30	6770	9.10	24.20	7380	16.4	6.54	7120	15.65	76.04
7*6*50	21790	11.80	79.39	23110	28	8.93	22046	23.6	84.18
8*7*60	26036	13.30	996.00	32276	35.8	11.86	30226	30.4	89.88
9*8*70	55390	15.30	2072.4	68020	43	14.50	67980	40.6	106.99

It is essential to use metaheuristic algorithms; hence, 12 stochastic examples were used. Table 6 reports the specifications of these examples. This study also used different MID, NPS, DM, SM, and solution times for better comparison. Figures 9-13 depict the output of mentioned indicators. Ten times of implementation and mean are reported as the final solution.

TABLE 6
SPECIFICATIONS OF 12 STUDIED STOCHASTIC PROBLEMS

Problem	Dimension	Problem	Dimension	Problem	Dimension
	i*r*t		i*r*t		i*r*t
1	5*4*30	5	10*8*45	9	14*9*55
2	7*6*50	6	11*8*45	10	15*10*55
3	8*7*60	7	12*8*50	11	18*10*60
4	9*8*70	8	13*9*50	12	20*15*70

As seen in these figures, the solution time of the NRGA algorithm is longer than the NSGA-II algorithm; hence, the NSGA-II algorithm is more appropriate. In terms of the rest of the indicators, NRGA outperforms in some cases, while NSGA-II outperforms in other cases. Hence, more accurate statistical analyses are required.

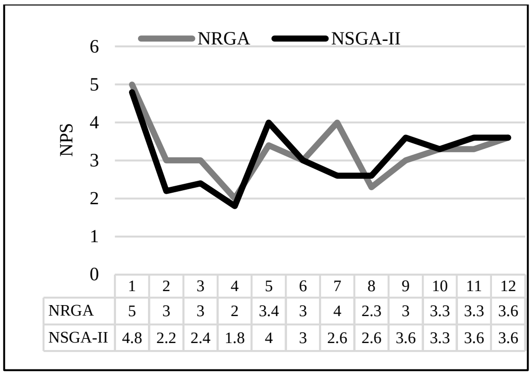

FIGURE 9
COMPARING ALGORITHMS IN TERMS OF NPS

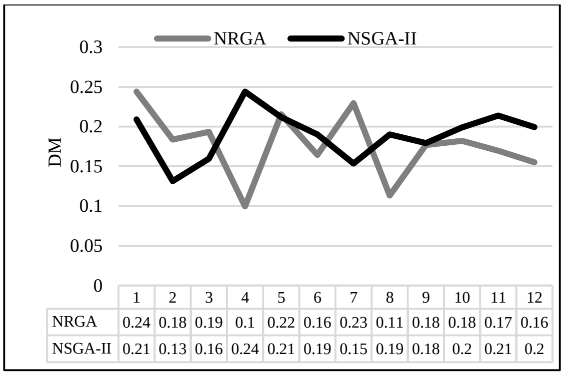

FIGURE 10
COMPARING ALGORITHMS IN TERMS OF DM

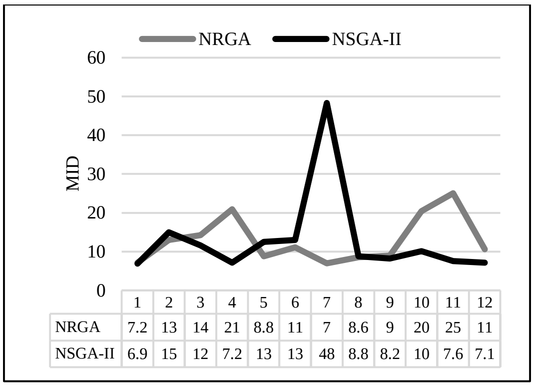

FIGURE 11
COMPARING ALGORITHMS IN TERMS OF MID

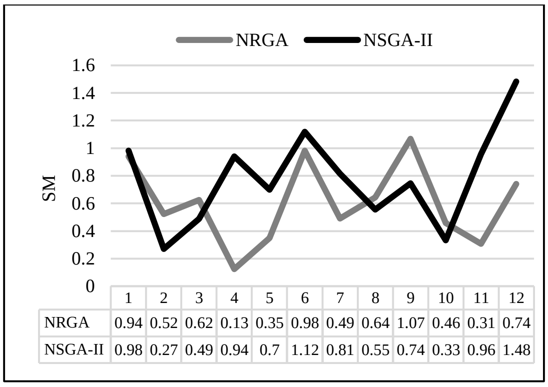

FIGURE 12
COMPARING ALGORITHMS IN TERMS OF SM

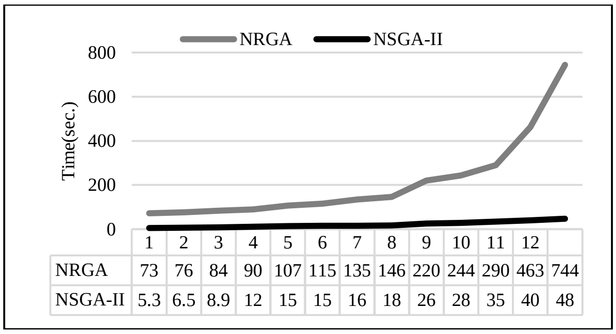

FIGURE 13
DIAGRAM OF COMPARING ALGORITHMS IN TERMS OF TIME

XVIII. Kruskal-Wallis Test

It is a nonparametric test for comparing mean values of more than two independent societies. This test does not assume that the response variable is distributed normally. Like many nonparametric tests, Kruskal-Wallis Test is done on data with rank or time scale when the sample size is small [37]. Therefore, this study conducted this test through Minitab 16 software. For this purpose, all data obtained from different societies are considered as a sample and then ranked. If repetitive observations exist in the mean values of their ranks, the researcher decides on the null hypothesis (H_0) regarding this he obtained statistical value. If $\alpha \geq p - value$ then H_0 (lack of significant difference between algorithm's mean values) is rejected. However, H_0 is not rejected when $\alpha \leq p - value$. This test was conducted at a level of α=0.05 for five criteria of NPS, DM, MID, SM, and Time.

TABLE 7
RESULTS OF THE KRUSKAL-WALLIS TEST

Algorithm	N	NPS		DM		MID		SM		Time	
		Median	P-value	Median	P-value	Median	P-value	Median	P-value	Median	P-value
NSGA-II	12	3.15	0.817	0.1795	0.436	10.888	0.436	0.5739	0.214	16.86	0.00
NRGA	12	3.15		0.1947		9.485		0.7795		140.48	

According to results reported in Table 7 and obtained P-values, NRGA and NSGA-II algorithms had no significant difference at the level of α=0.05 in terms of DM, NPS, MID, and SM metrics. However, these algorithms performed differently in terms of Time, and NSGA-II outperformed NRGA.

CONCLUSION

This paper investigate scheduling and planning surgery rooms and sterilization of RMDs for surgeries considering elective and emergency patients based on Mulvey's robust approach. This study minimize the total costs and completion time of the last surgery. The parameter of surgery length was taken indeterministic variable due to the high velocity of surgery length, different physical conditions of patients, and experiences or skills of surgeons. In addition to the AEC method, this study developed two metaheuristics algorithms for the mentioned purpose. Moreover, these two metaheuristic algorithms were compared based on five indicators, including the NPS, MID, SM, DM, and Solution Time. No significant difference was seen in the two algorithms regarding the mentioned metrics at a level of α=0.05 except for the solution time index in which, NSGA-II outperformed NRGA and solved the problem sooner. Because this problem is considered emergency patients and solution time is a critical factor in this case, it is suggested to use the NSGA-II algorithm.

MANAGERIAL INSIGHTS

Since the hospital managers seek to minimize the costs of the entire hospital in addition to providing proper service to the patients, they should identify the important and effective parameters, and manage various departments in an integrated manner instead of managing one department separately. In addition to saving time and money, this attitude makes it possible to use the available resources better and finally achieve the intended objectives. In this research, it is tried to consider the sterilization and surgery sections at the same time to minimize the costs and the last surgery completion time. By scheduling and planning the surgery rooms and the sterile unit, the completion time and the total cost of the surgeries will be reduced, which is less than the case where the scheduling and planning of the surgery room and the sterile unit are completely separate. Also, since in a hospital, as well as elective patients, there are emergency patients who need quick surgeries, it is necessary to use fast methods that can provide scheduling and planning for managers. Therefore, in this article, two meta-heuristic algorithms were presented that managers can use in their software or application systems. Among these two algorithms, the NSGA-II has worked better in terms of different indices. One of the most important limitations of this article was that unfortunately, despite various efforts, we could not get data from a hospital as a case study. The followings are recommendations for further studies: Considering other wards associated with operating rooms, such as the recovery unit, recovery bed, etc., cleaning operating rooms, scheduling surgeons, and presenting other algorithms compared to algorithms presented in the extant study.

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