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RESEARCH PAPER

Harmony Search Algorithm for Stochastic Operating Room Scheduling Considering Overhead Costs and Number of Surgeries

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ABSTRACT
Given the increasing human need for health systems and the costs of using such systems, the problem of optimizing health-related systems has attracted the attention of many researchers. One of the most critical cases in this area is operating room scheduling. Much of the cost of health systems is related to operating room costs. Therefore, planning and scheduling of operating rooms can play an essential role in increasing the efficiency of health systems as well as reducing costs. Given the uncertain factors involved in such matters, attention to uncertainty in this problem is one of the most critical factors in the results. In this study, the problem of the daily scheduling of the operating room with uncertain surgical time was investigated. For minimizing overhead costs and maximizing the number of surgeries to reduce patients' waiting time, after introducing a mathematical model, a chance-constrained programming approach is used to deal with its uncertainty. In this study, also, a harmony search algorithm is proposed to solve the model because of its NP-Hardness. By performing the numerical analysis and comparing the presented algorithm result with a genetic algorithm, the results show that the proposed algorithm has a better performance.

KEYWORDS: *Operating room scheduling; Health care; Chance-constrained modeling; Harmony search algorithm.*

1. Introduction

Due to the ever-changing lifestyle of people, as well as the changing pattern of patients and their needs, the provision of healthcare facilities and new ones are facing new challenges and obstacles. Due to the significant growth in healthcare costs, paying attention to these costs is an essential issue for all countries. One of the strategies that can be used to allocate appropriate resources and reduce costs is paying attention to management issues. Scheduling is one of the problems that has been of interest to researchers in various fields for many years. The operating room is one of the most critical parts of any hospital, where paying attention to scheduling can have very beneficial results [1]. Due to the close relationship between the operating room with other hospital departments and its impact on improving the performance of different departments, special attention should be paid to operating rooms and scheduling in these areas. Therefore, considering the crucial role of operating rooms in each hospital and the quality of services provided in these departments, it has become imperative to pay attention to the planning and scheduling of operating rooms. In this scheduling, many aspects, such as the patients scheduling, are taken into consideration. In operating room scheduling, each patient's waiting time is different, depending on the medical necessity and the physician's opinion. The patients are allocated to surgeons in such a way that the least delay in the surgical procedure is achieved. In addition to this objective, the maximum productivity of hospitals, the waiting times of patients, the increase in hospital income, etc., can be considered. The purpose of this study is to minimize overhead costs and maximize planned surgeries. In this area, there have been several different approaches, such as mathematical programming, simulation, heuristic, and meta-heuristic algorithms. The allocation and scheduling of operating rooms differ depending

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on the types of patients.
Although of much interest, the scheduling operating room problem has not received as much attention as nurse scheduling [2]. In this limited number of research, furthermore, most studies have considered elective patients whose surgery is pre-programmable, and a relatively limited number of patients was randomly selected in some studies. In this study, scheduling operations are performed for pre-selected patients. In some studies, the rate of patients' admission to the operating room has been considered definite. On the other hand, some researchers have tried to bring the results closer to real-world conditions, given the random conditions for the number of patients. But because of the complexity of solving the mentioned problems, some researchers have posed some unrealistic assumptions. Therefore, the final model solutions have been diverted from real-world situations.
The duration of surgical is an important topic due to its significant effect on surgical scheduling and operating room efficiency. Since several factors can affect it, for example, surgeon, surgeon experience, case type, case start time, etc. [3], in this study, in order to make the problem more realistic, the operation time is considered as probable and the probability distribution of the duration of surgical operations is predetermined. Additionally, the scheduling of surgical preparations is not dependent on the types of surgery and is supposed similar for each surgical operation. To solve this problem, after modeling it as mixed-integer programming, chance-constrained programming, and weighted *Lp*-metric method are used to deal with its uncertainty and multi-objectiveness, respectively. Since this problem is Np-hard [4], a harmony search algorithm is also proposed to solve it in real-size instances.
The following research is divided as follows: Section (2) presents a background of the study in this area. The proposed mathematical model is described in Section (3). Section (4) describes the harmony search algorithm used in the research. Following the introduction of the algorithm parameter tuning in Section (5), the numerical results are reported and, finally, conclusions are presented in Sections (6).

2. Literature Review

Fei et al. [5] proposed a weekly scheduling model to determine the surgical time of selected patients to minimize operating room idle time. The study assumes that each patient's surgeon is predetermined and has all the resources needed to operate except the surgeon at all hours and that conditions are available for recovery in the operating room if all recovery beds are employed. The scheduling problem is modeled using a two-stage flexible model. van Essen et al. [6] developed an innovative approach to emergency surgical scheduling. The purpose of this study was to minimize patients' waiting time. Lamiri et al. [7] provided weekly scheduling to determine the surgical time of selected patients in an emergency. In this study, the proposed problem was modeled with patients' medical costs and operating room overtime objective functions. The capacity of the emergency room was considered as a random variable. The solution technique used was Monte Carlo optimization. Vali-Siar et al. [8] considered a multi-period and multi-resource operating room scheduling. In this paper, it is assumed that patients are assigned to different days of the week and that only the ordering stage is performed. The scheduling of each patient's surgery was limited to two factors: the presence of the surgeon at the time and the time the test results were prepared. Denton et al. [9] provided the scheduling for only one operating room, in which model surgery time was uncertain. The proposed model is an extended model of Denton research, except that in the previous model, the patient arrangement was already known, and the aim was to determine the time of operation. In this study, three meta-heuristic algorithms were used for comparison.
Saremi et al. [10] presented a multi-stage mathematical model under uncertainty conditions. The objective function of this mathematical model was to reduce the waiting time. To solve the problem presented in their research, they utilized taboo search algorithms and simulated annealing optimization. The limitations of this approach include the prerequisites of public resource control and the number of recovery rooms. Other researchers in their papers examined the synchronization and scheduling of multiple operating rooms simultaneously [11, 12]. On the other hand, some researchers hypothesized that there would be an operating room in the hospital and modeled their mathematical model accordingly [13].
Hamid et al. [14] reduced patients' waiting time by reducing the time between two consecutive endings of surgery. They also randomly selected patients and eliminated the premise of choosing patients in their mathematical models. Researchers such as Al-Refaie et al. [15], Zhou et al. [16], and Roshanaei et al. [17] used exact

methods to solve the operating room scheduling problem. Saadouli et al. [18] used a meta-heuristic algorithm to solve the operating room scheduling problem. In this study, the ant colony algorithm was used, which compared the results with simulation to find out the efficiency of this algorithm. Other researchers have also focused on solving the operating room scheduling problem using different meta-heuristics and comparing the results [4, 19, 20, and 21].

Najjarbashi and Lim [22] proposed an approach, namely conditional value-at-risk, for operating room scheduling problem with uncertainty in which a surgery duration follows a probability distribution function. In this paper, to reduce variability in overtime, idle time, and associated costs, they proposed a stochastic mixed-integer linear programming model. Hamid et al. [23] incorporated the decision-making styles of the surgical team members in the operating room scheduling. They model the problem considering the availability of material resources, priorities of patients, and availability, skills, and competencies of the surgical personnel. Due to the Np-hardness of the problem, NSGA-II and MOPSO were applied to solve it. Ahmed and Ali [24] merged patient prioritization and patient scheduling. To model the problem as mixed-integer linear programming with nine objective functions, they used fuzzy TOPSIS employed to quantify patient preference for surgeons. Oliveira et al. [2] integrated patient preference in an operating room scheduling problem with elective patients. They proposed a mathematical model and used Urology Department at a University Hospital in Quebec City data in the proposed model a case study. For multifunctional operating rooms, Lin and Chou [25] studied a scheduling model considering three objective functions: utilization of the operating rooms, overtime-operating cost, and wasting cost for the idle time. After presenting a mathematical model to assign surgeries to the operating rooms within one week, they proposed a hybrid genetic algorithm with four local searches.

With a particular focus on the integration of downstream units, Santos and Marques [26] studied the master surgery scheduling problem which is the problem of assigning surgical specialties to operating room blocks. They proposed a Benders decomposition based on the stochastic programming model to penalize the overutilization of beds. Based on the parallel processing principle under uncertainty, Çelik et al. [27] considered the surgery scheduling of multiple operating rooms (OR) and induction rooms (IR). The authors proposed a two-stage stochastic mixed-integer programming model to minimize the expected total cost of patient waiting time, OR idle time and IR idle time. Park et al. [28] considered a cooperative operation scheduling in which multiple surgeons cooperatively manage patients. To minimize both the number of ORs used and the overtime, while providing a satisfactory result based on surgeons' OR preferences in a Korean university hospital with 32 ORs, they proposed a mathematical programming model. Lotfi and Behnamian [29] studied the operating room scheduling of hospital networks with a virtual alliance with cooperation and competition among the agents. By considering the conditions of emergency arrival, the time of inter-hospital transportation, and the elective patients and non-elective patients in the scheduling, they proposed a mixed-integer mathematical programming and a multi-objective learning variable neighborhood search algorithm to minimize total completion of surgeries, the cost of allocating the patient to the hospital and the surgeon, and the cost of overtime operating rooms throughout the network. Azar et al. [30] proposed a time-indexed model to solve the operational scheduling problem. In the form of the chance constraints model, they developed specific constraints that improve the schedule, reducing the need for overtime without affecting the utilization significantly. Bargetto et al. [31] studied an integrated operating room planning and scheduling problem with human resources other than surgeons, i.e., nurses. In that research, after proposing a model for sequence-dependent operating room cleaning times, they devised a branch-and-price-and-cut algorithm with a cutting procedure, inspired by Benders' decomposition. Wang et al. [32] provided a literature review on comparing outpatient surgery scheduling with inpatient surgery scheduling. Furthermore, recently, Shehadeh and Padman [33] focused on stochastic optimization approaches for elective surgery scheduling and downstream capacity planning.

According to the literature review, no research has been conducted on operating room scheduling under uncertainty and on operating room overhead costs. Therefore, this study investigates this issue by simultaneously considering the objectives of minimizing overhead costs and maximizing the number of surgeries and the uncertain duration of surgery. For solving this problem, a chance-constrained model and a harmony search algorithm are suggested.

3. Problem Definition and Modeling

In this study, it is assumed that there are several surgeons in a hospital who perform surgeries based on the scheduling performed by the hospital management. All operating days of the week in the operating rooms of this hospital are assigned to surgical teams, each consisting of several surgeons. After the patient visits the surgeon and recognizes the need for surgery, the patient's name is announced to the operating room management and the operating room then finalized the list of operations the next day and announcing to the surgeon. Every day, operations are performed on a timely basis, and follow-up steps are taken. Each operation also requires equipment that is available after sterilization.

Among the limitations that should be considered in such research are the number of operating rooms and the number of surgeons available. The purpose of this research is the scheduling the operating rooms with the following goals:

- Minimizing overhead costs caused by unemployment and overtime in operating room staff
- Maximizing the number of surgeries

The constraints of this study are as follows:

- Limitations on patient assignment to the surgeon
- Operating room restrictions
- Limitation of surgical resources

The assumptions used in this research are presented below:

- Patients and surgeons must be available from the beginning of the scheduling period.
- Every patient needs only one surgeon who works with a team of nurses.
- Except for the surgeon and the operating room, other resources such as beds, recovery, and so on are available.
- The duration of surgery is random. In this case, the duration of operation has a uniform distribution.

3.1. Mathematical modeling

In the following, the proposed mathematical model is introduced. The used sets in this research are defined as follows:

The sets used in this research are defined as follows:

p:	The set of patients who need surgery	$p \in \{1,2,\dots,P\}$
s:	Index of Surgeons	$s \in \{1,2.\dots,S\}$
o:	Operating Room Index Set	$o \in \{1,2,\dots,O\}$

The parameters used in this research are defined as follows:

T_o:	Overtime cost per hour for operating room *o*
A_s :	The binary parameter that takes one if the surgeon *s* is available
pos_{po}:	A binary variable that takes one if it is possible to perform surgery on the patient *p* in room o
$\tilde{t}_p$:	Duration of surgery for patient *p* (random parameter)
r_p:	Duration of recovery for the patient *p*
H_O:	Working time of operating room *o*
H_s^{max}:	Maximum surgical time for the surgeon *s* in a day
tar_o^{max}:	The maximum overtime for operating room *o* in a day
pat_s:	Patient set for surgeon *s*

Problem decision variables are defined as follows:

x_{po} :	A binary variable that takes one if the patient *p* is in the operating room *o*
$ss_{p'p}$:	The binary variable that takes one if the patient *p* after the patient *p'* undergoes surgery
$ss_{o,p+1,s}$:	The binary variable that takes one if the surgeon *s* does not perform any surgery
$sr_{pp'o}$:	A binary variable that takes one if the patient *p'* after the patient *p* is operated on in the operating room *o*
$ss_{p,p+1,o}$:	The binary variable that takes one if the patient *p* is in the room *o* as the first surgical patient
ss_{0po}:	The binary variable that takes one if the patient *p* is in the room *o* as the final surgical patient
$ss_{o,p+1,0}$:	The binary variable that takes one if no surgery is performed in the operating room *o*
ct_p:	Patient's surgical completion time
idl_o:	Room idle time
tar_o:	The overtime for operating room *o*

$ss_{p,p+1}$: Patient p is selected for the first surgery in the surgeon's sequence

ss_{op}: Patient p is selected for the last surgery in the surgeon's sequence in the room o

The mathematical model presented in this research is as follows:

$$min \sum_{o=1}^{O} T_O\, tar_o + I_o idl_o \tag{1}$$

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

s.t:

$$\sum_{o=1}^{O} x_{po} \leq A_s \qquad s \in \{1,2,\dots,S\}, p \in pat_s \tag{3}$$

$$x_{po} \leq pos_{po} \qquad p \in \{1,2,\dots,P\}, o \in \{1,2,\dots,O\} \tag{4}$$

$$\sum_{p \in pat_s} \sum_{o=1}^{O} x_{po}\,(\tilde{t}_p) \leq H_s^{max} \qquad s \in \{1,2,\dots,S\} \tag{5}$$

$$\sum_{o=1}^{O} x_{po} = ss_{0p} + \sum_{\substack{p \in pat_s \\ p \neq p}} ss_{\acute{p}p} \qquad s \in \{1,2,\dots,S\}, p \in pat_s \tag{6}$$

$$\sum_{o=1}^{O} x_{po} = \sum_{\substack{\acute{p} \in pat_s \\ p \neq p}} (ss_{p\acute{p}} + ss_{p.p+1}) \qquad s \in \{1,2,\dots,S\}, p \in pat_s \tag{7}$$

$$\sum_{p \in pat_s} \left(ss_{0p} + ss_{0.p+1.s}\right) = 1 \qquad s \in \{1,2,\dots,S\} \tag{8}$$

$$ss_{0.p+1.s} + \sum_{p \in pat_s} ss_{p.p+1} = 1 \qquad s \in \{1,2,\dots,S\} \tag{9}$$

$$x_{po} = \sum_{\substack{\acute{p}=0 \\ p \neq \acute{p}}} sr_{p\acute{p}o} \qquad p \in \{1,2,\dots,P\}, o \in \{1,2,\dots,O\} \tag{10}$$

$$x_{po} = \sum_{\substack{\acute{p}=1 \\ p \neq \acute{p}}}^{p+1} sr_{p\acute{p}o} \qquad p \in \{1,2,\dots,P\}, o \in \{1,2,\dots,O\} \tag{11}$$

$$\sum_{p=1}^{p+1} sr_{0po} = 1 \qquad o \in \{1,2,\dots,O\} \tag{12}$$

$$\sum_{p=0}^{p} sr_{p.p+1.o} = 1 \qquad o \in \{1,2,\dots,O\} \tag{13}$$

$$\tilde{t}_p + ct_{\acute{p}} + r_{\acute{p}} + \left(ss_{\acute{p}p} - 1\right)M \leq ct_p \qquad o \in \{1,2,\dots,O\}, p, \acute{p} \in \{1,2,\dots,P\}, \acute{p} \neq p \tag{14}$$

$$\tilde{t}_p + \left(ss_{0ps} - 1\right)M \leq ct_p \qquad s \in \{1,2,\dots,S\}, p \in pat_s \tag{15}$$

$$\tilde{t}_p + ct_{\acute{p}}\left(sr_{\acute{p}po} - 1\right)M \leq ct_p \qquad o \in \{1,2,\dots,O\}, p.\acute{p} \in \{1,2,\dots,P\}, \acute{p} \neq p \tag{16}$$

$$\tilde{t}_p + \left(sr_{0po} - 1\right)M \leq ct_p \qquad p \in \{1,2,\dots,P\}, o \in \{1,2,\dots,O\} \tag{17}$$

$$ct_p + \left(x_{po} - 1\right)M - H_o \leq tar_o \qquad s \in \{1,2,\dots,S\}, p \in pat_s \tag{18}$$

$$H_o + tar_o - \sum_{p=1}^{p} x_{po}\,(\tilde{t}_p) \le idl_o \qquad o \in \{1,2,\dots,O\} \tag{19}$$

$$tar_o\,.\,idl_o \ge 0 \qquad o \in \{1,2,\dots,O\} \tag{20}$$

$$tar_o \le tar_0^{max} \qquad o \in \{1,2,\dots,O\} \tag{21}$$

$$x_{po} \in \{0.1\} \qquad p \in \{1,2,\dots,P\}, o \in \{1,2,\dots,O\} \tag{22}$$

$$ss_{\acute{p}p} \in \{0.1\} \qquad o \in \{1,2,\dots,O\}, p, \acute{p} \in \{1,2,\dots,P\}, \acute{p} \ne p \tag{23}$$

$$ss_{0ps} \in \{0.1\} \qquad s \in \{1,2,\dots,S\}, p \in pat_s \tag{24}$$

$$ss_{p.p+1.s} \in \{0.1\} \qquad s \in \{1,2,\dots,S\}, p \in pat_s \tag{25}$$

$$ss_{0.p+1.s} \in \{0.1\} \qquad s \in \{1,2,\dots,S\} \tag{26}$$

$$sr_{\acute{p}po} \in \{0.1\} \qquad \acute{p} \in \{0,\dots,P\}, p \in \{1,\dots,p+1\}, .\acute{p} \ne p, \; o \in \{1,2,\dots,O\} \tag{27}$$

$$ct_p \ge 0 \qquad p \in \{1,2,\dots,P\} \tag{28}$$

Equations (1) and (2) as objective functions of the scheduling problem, minimized the overhead costs and maximized the number of scheduled surgeries, respectively. Equation (3) guarantees that any surgery is scheduled if only the surgeon is present that day. Equation (4) assigns each operation to the appropriate operating room. Equation (5) ensures that the maximum number of hours of surgery for each surgeon is no more than its upper bound. Equations (6) and (7) represent the sequence constraint for the surgical operation for each surgeon. Constraint (8) and (9) guarantee that to each surgeon at least one surgery is assigned. Equations (10), (11), (12), and (13) are related to the sequence of operations in the operating room. Equations (14) to (17) determine the completion time of scheduled operations. This time should be at least the same as the total surgical and postoperative recovery time of the current patient and the previous patient. Equations (18) and (19) are used to calculate idle time and overtime. Equations (20) to (28) specify the type of decision variables in this model.

Note that, in this model, (*i*) dummy patients are used at the beginning and the end of the sequence for surgery rooms, (*ii*) patients included in this scheduling are only those patients who are pre-selected and need surgery, and (*iii*) the emergency patients treated without surgery are not included in this scheduling.

3.2. Chance-constrained programming

Suppose that the duration of surgery has a uniform distribution between a_p and b_p. Aim to get the value $(\tilde{t}_p)_\alpha$ such that $\left(\tilde{t}_p - (\tilde{t}_p)_\alpha\right) = 1 - \alpha$.

$$prob\left(\tilde{t}_p - (\tilde{t}_p)_\alpha\right) = 1 - \alpha \to \int_{\alpha}^{(\tilde{t}_p)_\alpha} U(a_p.b_p)dx = (1-\alpha) \to \frac{(\tilde{t}_p)_\alpha - \alpha}{b_p - a_p} = 1 - \alpha \tag{29}$$

$$(\tilde{t}_p)_\alpha = \alpha \times a_p + (1-\alpha) b_p \tag{30}$$

where α-1 is the probability that can be considered for the constraints and it indicates the probability of constraints' satisfaction. Now, we have Constraint (31).

$$\sum_{p \in pat_s} \sum_{o=1}^{O} x_{po} \times \alpha \times a_p + (1-\alpha) b_p \le H_s^{max} \tag{31}$$

This way, the definitive model is transformed as follows, after which the model is finalized. Chanced-based constraints are as follows:

$$\sum_{p \in pat_s} \sum_{o=1}^{O} x_{po} \times (a_p \times \alpha + b_p(1-\alpha)) \le H_s^{max} \qquad s \in \{1,2,\dots,S\} \tag{32}$$

$$a_p \times \alpha + (1-\alpha) + ct_{\acute{p}} + r_{\acute{p}} + \left(ss_{\acute{p}p} - 1\right)M \le ct_p \qquad o \in \{1,2,\dots,O\}, p, \acute{p} \in \{1,2,\dots,P\}, \quad \acute{p} \ne p \tag{33}$$

$$a_p \times \alpha + b_p(1-\alpha) + (ss_{0ps} - 1)M \le ct_p \quad s \in \{1,2,\dots,S\}, p \in pat_s \tag{34}$$

$$a_p \times \alpha + b_p(1-\alpha) + ct_{\acute{p}} + (sr_{\acute{p}po} - 1)M \le ct_p \quad o \in \{1,2,\dots,O\}, p, \acute{p} \in \{1,2,\dots,P\}, \acute{p} \ne p \tag{35}$$

$$a_p \times \alpha + b_p(1-\alpha) + (ss_{0po} - 1)M \le ct_p \quad p \in \{1,2,\dots,P\}, o \in \{1,2,\dots,O\} \tag{36}$$

$$H_o + tar_o - \sum_{p=1}^{P} x_{po}\,(a_p \times \alpha + b_p(1-\alpha)) \le idl_o \quad o \in \{1,2,\dots,O\} \tag{37}$$

3.3. Multi-objective optimization

In this study, the weighted *Lp*-metric method was used to transform the multi-objective problem into a single-objective problem. In multi-objective problems, after solving the model, there will be a set of solutions called the Pareto layer, but in this way, we will achieve a final solution by integrating the objective functions in which a distance function, as Equation (38), is applied to measure the closeness between a solution and the ideal point [34].

$$f(x) = Min(w\left(\frac{f_2^* - f_2}{f_2^*}\right)^p + (1-w)\left(\frac{f_1^* - f_1}{f_1^*}\right)^p)^{1/p} \tag{38}$$

where f_1 and f_2 are the first and the second objective function of the presented model, respectively. Furthermore, $f_1^*$and f_2^* are the optimal values of the first and the second objective function. w_i indicates the degree of importance (weight) of each objective function and p is a norm of Equation (38).

3.4. A numerical instance

In order to validate the proposed model, in this subsection, an instance with 10 patients, 3 surgeons and 8 operating rooms is solved. To solve the model, the GAMS 24.9.1 software with CPLEX solver is used. Here, it is assumed that $pos_{po} = 1$ and other information are given in the following. The selected norm in the Lp-metric method was *P= 1* and the results are shown in Figure (1).

According to this result, the contradiction between the objective function of minimizing the overhead costs (z_1) and maximizing the number of surgeries (z_2) is quite obvious. As a result, if the decision-maker is more focused on increasing the number of surgeries, the system will have to spend more for this purpose. So the objective function here is to increase surgeries while reducing costs.

T_o: /o1 5, o2 3, o3 6, o4 7, o5 4 , o6 8,o7 9, o8 10 /

H_s^{max}: /s1 30 , s2 25, s3 40, s4 21, s5 22/

A_s : /s1 1, s2 1, s3 1,s4 1,s5 1/

tar_o^{max}: /o1 10, o2 20, o3 30, o4 40, o5 50, o6 60, o7 20, o8 35/

r_p: /p1 4,p2 4,p3 4,p4 5,p5 3,p6 4,p7 7,p8 8,p9 9,p10 10/;

H_O :uniform(5,10)

$\tilde{t}_p$: uniform(3,10)

r_p: uniform(5,10)

w_1	w_2	z_1	z_2
0	1	202.14	7
0.1	0.9	160.011	6
0.2	0.8	160.011	6
0.3	0.7	142.485	5
0.4	0.6	142.485	5
0.5	0.5	122.809	4
0.6	0.4	122.809	4
0.7	0.3	118.179	3
0.8	0.2	118.179	3
0.9	0.1	118.179	3
1	0	118.179	3

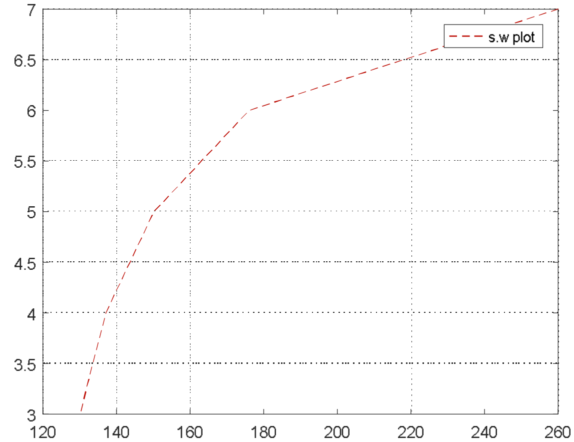

Fig. 1. A numerical example

4. Harmony Search Algorithm

Due to our problem is NP-Hard [35], the harmony search algorithm (HM) for solving the problem have been compared in large-size instances. This algorithm is one of the meta-heuristic algorithms, whose main idea is derived from the process of creating music to achieve a final note that is harmonious [36]. In this algorithm, several initial solutions are generated and stored in harmony memory, and the best of them is selected, and the process continues with a predefined number. Initially, the basic parameters of this algorithm must be adjusted, which will be described in more detail below. To this end, the method of solution representation is described first, followed by the details of the algorithm.

4.1. Solution representation

The way the response is presented should be in a way that demonstrates the allocation of the operating room and the surgeon at the same time. Assuming p is the number of patients assigned to room o and s the number of surgeons assigned to room o and O is the total number of operating rooms, the solution is a matrix $O \times \max\{p^o + s^o - 1\}$ so that $O \in \{1.2. \dots . O\}$.

There are $s - 1$ operating rooms here; in fact, the rows of each matrix represent each operating room. In this way of solution representation, "*" is used to separate surgeons and "–" to mark surgeons who have not been assigned to surgery. The numbers in the matrix represent the number of patients. For example, a problem with three operating rooms and ten patients in each room with three, two, and two surgeons, respectively, are presented in the matrix below. As shown in Figure (2), among these 10 patients, patients 1, 3, and 6 are operated on in room 1 and it is clear that patient 1 is operated by surgeon 1 in room 1. It should be noted that the sequence of patients is in the order of numbers appearing from left to right.

O_1	1	*	3	*	6
O_2	2	5	*	8	0
O_3	4	7	9	*	-

Fig. 2. Solution representation

4.2. Initialization

The initial process consists of the initial value of the parameters and the initial value of the HM. The five parameters of the harmony search algorithm are:

1. Pitch Adjustment Rate (PAR)
2. Number of decision variables (N)
3. Maximum number of Initial solution (NI)
4. Harmonic Memory Size (HMS)
5. Harmony Memory Consideration Rate (HMCR)

In this study, the PAR value is 0.9 for small and medium-size instances and 0.95 for large-size instances. It should be noted that these values are obtained by parameter tuning by the Taguchi method. HM is the number of harmonic memory that holds a certain number of solutions. In this study, the value of 20 for this parameter is considered for small and medium problems and 30 for large problems. Finally, the HMCR, which indicates the probability of selecting the solution from the HM, should be placed. Very small HMCR values reduce the performance of the algorithm to a random search algorithm. In small and medium-size instances, the value is 0.9, and in the big problems, it is 0.95 for HMCR. HM is a two-dimensional matrix with an HMS row and $N + 1$ columns in which the target function for each solution vector is specified in the last column.

Tab. 1. Harmony memory (HM)

Y_{11}	Y_{12}	$\cdots$	Y_{1N}	$f(Y_1)$
Y_{21}	Y_{22}	$\cdots$	Y_{2N}	$f(Y_2)$
$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$
$Y_{HMS-1,1}$	$Y_{HMS-1,2}$	$\cdots$	$Y_{HMS-1,N}$	$f(Y_{HMS-1})$
$Y_{HMS,1}$	$Y_{HMS,2}$	$\cdots$	$Y_{HMS,N}$	$f(Y_{HMS})$

Table (1) shows a sample of HM where Y is a decision variable in the vector Y. Each row of this matrix represents a solution to the problem. Here, $f(Y)$ is the value of the objective function for each solution.

4.3. Generating new harmonies

In this algorithm, like the genetic algorithm, it is necessary to use different operators as described below. Initially, a random number is generated to generate the initial solution. The random number generated is compared to the value of HMCR, and if the value is smaller, the first solution is selected from the harmonic memory. Otherwise, it will be randomly generated. This process is then repeated until the harmonic memory is filled in. If the chosen solution is selected from the harmonic memory, a random number should be re-generated and compared with the value of PAR. If the number produced is smaller than the value of PAR, the solution chosen will be changed according to Equation (39). To determine the value of change on the selected variable from the matrix memory, another parameter is called *bw,* which is obtained by Relation (2) of the new variable value (Doush et al., 2018).

$$X_{new} = X_{old} + bw \times \varepsilon \tag{39}$$

Here X_{old} as the value of the variable stored in the harmonic memory, and X_{new} appears as the new variable after the adjustment operation. In fact, ε is the random number of a uniform distribution in [-1, 1]. Figure (3) shows how to modify the selected harmonics from memory.

O_1	1	*	3	*	6
O_2	2	5	*	8	10
O_3	4	7	9	*	-

O_1	1	*	3	*	6
O_2	2	15	*	8	10
O_3	4	7	9	*	-

Fig. 3. New harmony

Therefore, two HMCR and PAR operators are used to generate a new harmony. The following provides an example of how these operators work:

Step 1: A random number is generated in the interval [0,1]. In this example, it is 0.3.

Step 2: This random number is compared with the value of the HMCR parameter, whose value in this example is assumed to be 0.7.

Step 3: Given that the random number is less than the HMCR parameter (0.7> 0.3). Therefore, a solution from the harmony memory randomly is selected.

Step 4: Another random value is generated that assumes the value is 0.4. It is then compared with the PAR parameter set to 0.3. Since the random number is greater than the PAR parameter, the selected solution as the new solution replaces the previous one.

4.4. Updating the harmony memory (HM)

Likewise, all the solutions in the harmonic memory are generated. Then the value of that harmony is calculated according to the fitness function and compared with the worst harmony in the matrix memory. If it is better than the worst harmony in the harmony memory, the new harmony replaces the previous one.

4.5. Stopping criteria

In this study, the criteria for stopping is to reach a certain level of repetition. In the large-size instances, 200 repetitions, and in the medium and small-size instances, 100 repetitions were considered.

5. Computational Results

In order to verify the model and the HM algorithm in small-size instances, the results of them had been compared. Furthermore, in order to evaluate the effectiveness of the algorithm proposed in the previous section in large-size instances, we compared it with the Genetic algorithm [25]. The metaheuristic algorithm was implemented in MATLAB software 2013 and the mathematical model is coded in GAMS 25.0.2

and run on an Intel Core i7@ 3.5 GHz PC with 8 GB RAM under a Microsoft Windows 10 environment.

5.1. Evaluation metrics

In single-objective optimization problems, the final output is a solution that has the best objective function for all the solutions. But in the multi-objective problem, the evaluation method is different and cannot be evaluated as a single objective. Accordingly, criteria are needed to assess the quality of the final responses. In this study, three essential criteria are used to evaluate the last solutions of the algorithms, which will be described below [37].

- **Mean of Ideal Deviation (MID):** In this criterion, an ideal solution is first considered for the problem, and then the mean deviations of the Pareto set of ideal solutions are calculated. The ideal solution is a state in which both solutions are at the same optimal value. The equation is defined as follows:

$$MID = \frac{\sum_{i=1}^{n} C_i}{n} \tag{41}$$

In the above relation, n is the number of Pareto solutions, and the value of C_i is calculated from the following equation. Given that the first objective function is the minimization type and the second objective function is the maximization type, to determine the ideal point, convert the maximum objective function to the minimum and convert the point (0.0) as Consider an ideal point. Clearly, the lower the MID criterion, the better the algorithm's performance.

$$C_i = \sqrt{(f_{1i} - f_1^*)^2 + (\frac{1}{f_{2i}} - \frac{1}{f_2^*})^2} \tag{42}$$

- **Spread of Non-Dominance Solution (SNS):** This indicator indicates the amount of variation in the responses. This index is defined as Equation (43). Having a high amount of SNS indicates better algorithm performance.

$$SNS = \sqrt{\frac{\sum_{i=1}^{n} (MID - C_i)^2}{n-1}} \tag{43}$$

- **Rate of Achievement to two objectives simultaneously (RAS):** Another evaluation criterion proposed in this study is RAS. The RAS equation is shown below. Having the lower values, RAS means that the algorithm is better.

$$RAS = \frac{\sum_{i=1}^{n} (\frac{f_{1i} - F_i}{F_i}) + (\frac{F_i - f_{2i}}{F_i})}{n} \tag{44}$$

5.2. Parameters tuning by taguchi method

In the Taguchi method, the factors influencing the test result are divided into two uncontrolled (*N*) and under-controlled (*S*) groups. Then an S/N variable is defined, which is called the signal ratio. The Taguchi method of setting parameters adjusts the factors to levels that maximize the *S/N* ratio. If the problem is minimization, the value of *S/N* is calculated from the following Equation [38].

$$S/_{N} = -10\, log_{10}(\frac{\sum_i Z_i^2}{n}) \tag{45}$$

where z_i is the response variable in experiment i, and n represents the number of experiments. In the harmony search algorithm, HMS (Harmony Memory Size), HMCR (Harmony Memory Consideration Rate), PAR (Pitch Adjustment Rate), BW (Band Width) are the four factors that influence the quality of the solution. One of the essential uses of meta-heuristic algorithms is the adequate tuning of algorithm parameters because the performance of a proper algorithm with an incorrect parameter setting can be significantly reduced. Table (2) presents the levels defined for each parameter in the harmony search algorithm.

Tab. 2. Levels tested HS parameters for small and medium-size instances

HS parameters	Low	Medium	High
HMS	10	20	30
HMCR	0.9	0.95	0.99
PAR	0.6	0.8	0.9
B.W	0.5	0.6	0.7

Figure (4) shows the results of parameter tuning for small and medium-size instances in the harmony search algorithm.

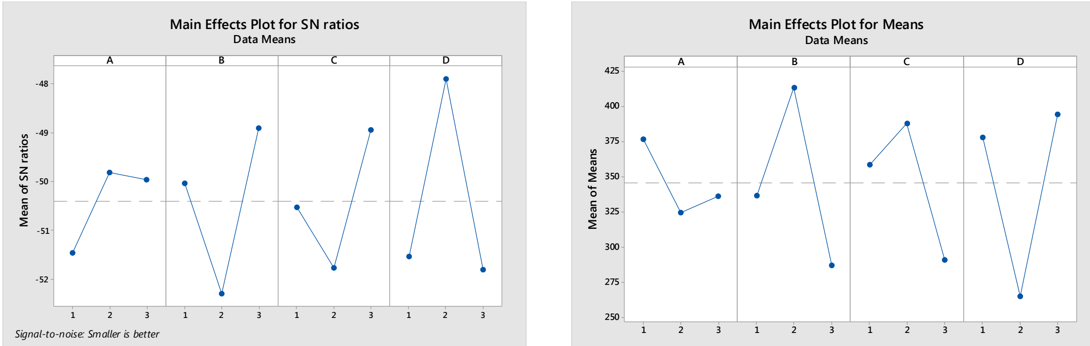

Fig. 4. Diagrams of harmony search algorithm parameters for small and medium-size instances

By comparing MID values, it can be concluded that parameter A at level 2 has the least deviation from the best solution. The same result can be obtained for parameters B, C, D at levels 3, 3, and 2, respectively. The same results can be observed with the S/N diagram; for example, parameter A at level 2 has the highest S/N ratio compared to other levels. The same can be done for large-size issues.

Tab. 3. Levels of HS parameters for large-size instances

HS parameters	Low	Medium	High
HMS	10	25	30
HMCR	0.9	0.95	0.99
PAR	0.7	0.8	0.95
B.W	0.6	0.7	0.8

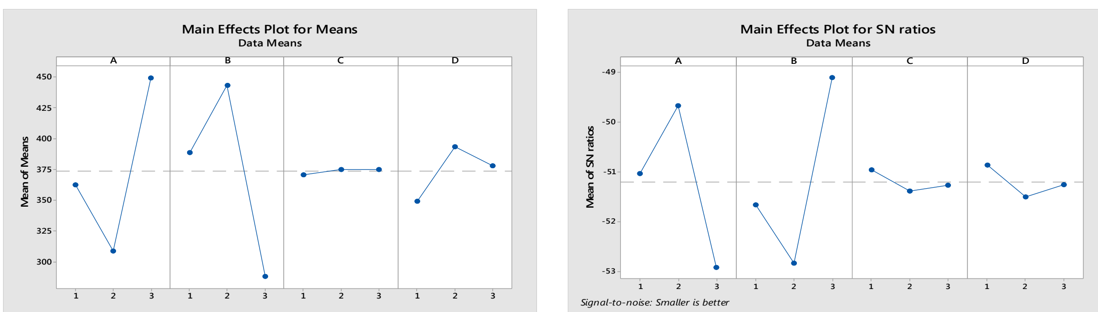

Fig. 5. Harmony search algorithm parameter tuning for large-size instances

Figure (5) presents the results of the parameter tuning of large-size instances for the harmonic search algorithm. Therefore, it can be concluded that parameter A at level 3 and parameter B at level 2 have the least deviation for the best solution. In C and D parameters, there is no significant difference between levels 2 and 3, respectively, so considering the time of running the algorithm, level 3 is considered for both settings. The final result of parameter tuning by the Taguchi method is presented in Table (4).

Tab. 4. Result of parameters tuning for the proposed harmony search algorithm

Problem size	HMS	HMCR	PAR	B.W
Medium-size instance	20	0.99	0.9	0.6
Large-size instance	30	0.95	0.95	0.8

5.3. Numerical results

After adjusting the parameters of both proposed algorithms by the Taguchi method described in the previous section, in this section, the stochastic problems of small, medium and large-size instances are evaluated according to the defined criteria. The values obtained are shown in Table (5).

Tab. 5. Evaluation of solution for research algorithms based on problem size and index type

Problem size		Algorithms and index					
		MID		SNS		RAS	
s	*p*×*o*	HS	GA	HS	GA	HS	GA
3	4*4	296.95	318.69	74.05	27.56	0.6	0.56
	4*5	191.60	208.39	190.73	54.55	0.42	0.27
	5*4	270.26	141.45	109.65	32.25	0.67	0.46
	5*5	163.29	356.93	145.50	76.09	0.04	0.27
	6*6	273.76	187.30	110.28	55.89	0.47	2.05
	Average	239.17	242.55	126.24	49.27	0.44	0.722
3	10*6	486.24	610.24	321.43	297.11	1.62	1.67
	10*7	576.74	600.56	149.19	63.01	1.55	0.92
	10*8	648.36	290.60	255.98	77.17	5.29	0.66
	10*9	158.07	243.90	142.76	148.67	1.7	2.46
	10*10	163.21	580.27	270.84	212.45	0.49	11.2
	12*6	335.82	340.92	206.87	128.27	1.06	2.73
	12*7	220.41	293.56	238.91	195.38	1.75	0.21
	12*8	218.57	254.90	183.06	161.14	0.59	1.65
	12*10	500.79	383.97	262.10	159.15	0.67	0.095
	12*9	237.27	363.62	145.06	129.3	0.047	2.42
	Average	354.54	396.15	217.72	157.17	1.47	1.49
3	20*6	332.12	625.74	231.23	263.57	1.67	2.05
	20*7	384.29	712.49	148.63	67.61	1.24	0.54
	20*8	269.06	426.58	123.72	115.71	0.92	2.77
	20*9	513.60	718.39	288.76	257.91	0.14	2.05
	20*10	239.40	727.32	264.55	267.93	0.51	1.4
	30*6	463.38	606.06	286.98	269.97	1.72	2.7
	30*7	599.20	678.86	264.74	285.25	1.3	1.23
	20*11	407.29	699.97	286.79	274.96	1.03	2.08
	40*6	294.49	609.83	215.61	250.08	1.98	1.64
	40*7	388.05	713.39	284.42	61.11	0.052	0.042
	Average	385.12	652.86	239.64	211.91	1.056	1.79

By examining the presented results, the harmony search algorithm in the two indices yields better results than the genetic algorithm. In small-size instances, the MID value is not significantly different for both algorithms, but in large-size instances, as can be seen, the harmony search algorithm has a lower MID than the genetic algorithm. As shown in the table, in all of the problems solved, the value of the SNS index in the harmony search algorithm is higher than in the genetic algorithm. Therefore, the harmony search algorithm performs better than the genetic algorithm according to the SNS index. But in terms of the RAS index, in most of the problems solved, except for some problems, the harmony search algorithm has a lower RAS value than the genetic algorithm, but this difference is not large in all size instances, and it is not possible to decide on the performance of the two algorithms according to RAS index. Therefore, there is no significant difference between the two algorithms.

In this section, a comparison between the algorithms for analyzing the results obtained based on efficiency criteria is provided. As it is clear from the results table, the harmony search algorithm has provided acceptable results in two indicators.

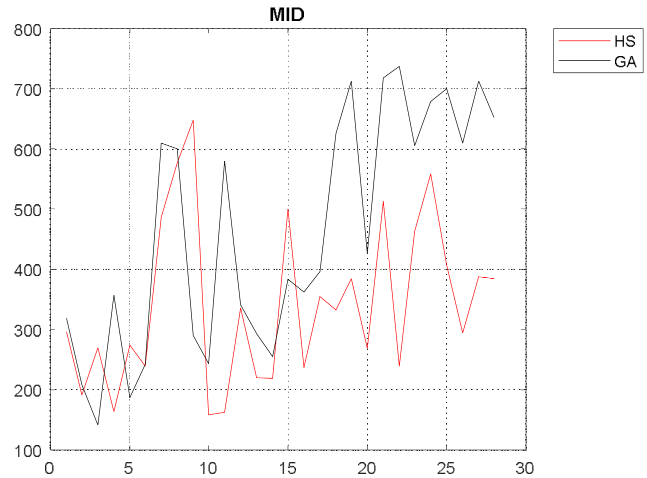

Fig. 6. The MID index comparison chart for genetic algorithm and harmony search

In small dimensions, the MID index of the GA and HS algorithm does not differ much, but as the dimensions of the instances increase, this difference increases and as it can be seen, the HS algorithm has a lower MID than the GA. Considering that the reason for using the meta-heuristic algorithm is to solve instances in large dimensions, it is better to use an algorithm that has less MID in instances with large dimensions.

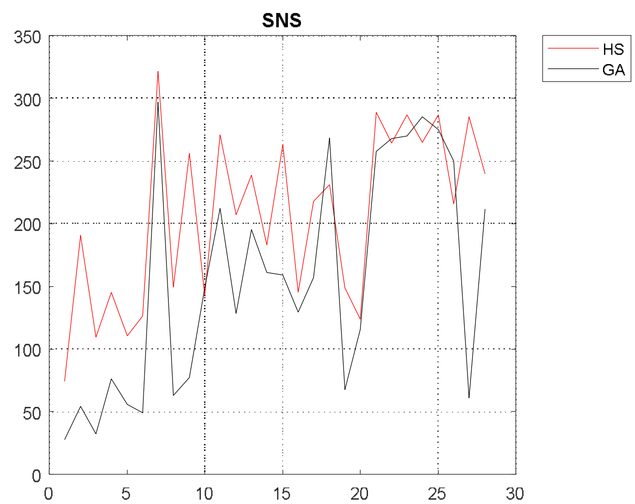

Fig. 7. The SNS index comparison chart for genetic algorithm and harmony search

As it is clear in Figure 7, in all the instances that were solved, the value of the SNS index in the HS algorithm is higher than the GA algorithm and since an algorithm with a higher value in the SNS index has better performance, the HA performs better than GA in this index.

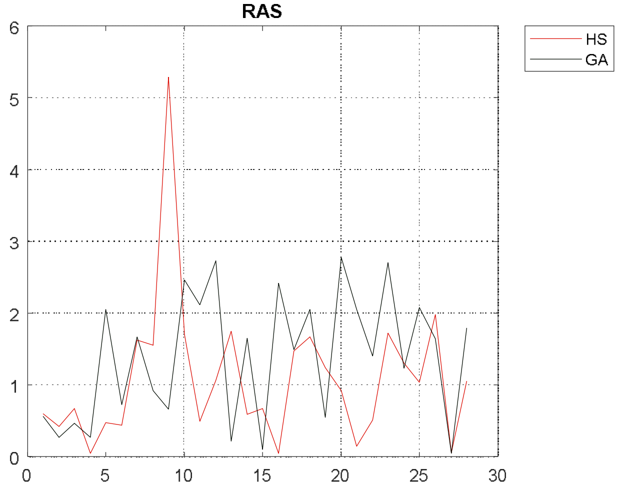

Fig. 8. The RAS index comparison chart for genetic algorithm and harmony search

Figure 8 shows that in most of the instances that were solved, the RAS of the HS algorithm has a lower value than the GA algorithm, but it seems that this difference is not a significant one, and as a result, it is necessary to provide complete statistical analyzes to analyze the results in the next subsection.

5.4. Analysis of variance

In the present study, the ANOVA test is used to evaluate the performance of the algorithms. The condition for using this test is the equality of variances and normality of the data. The data must be $P-VALUE \geq 0.01$ to be normal. According to the results below, the probability value for this test is 0.023 for the genetic algorithm and 0.15 for the harmonic search algorithm. Therefore, the normality of the data cannot be ruled out by this test. For equality of variances, the condition $P-VALUE \geq 0.05$ is required, as the results in the following diagrams show. According to the presented results, the F-value is 0.108, and the significant probability is 0.51, so we cannot reject the assumption of the equality of variance between the two populations. So, according to the above information, the variance of the two algorithms is equal. In this section, we intend to evaluate the results for both algorithms. This section uses ten different example instances, each of which is executed ten times, and the mean of values is reported as a result. To analyze the variance in this study, if the $\alpha \geq p-value$ is established, then the hypothesis H_0 (absence of significant difference between the averages of the algorithms) is rejected, but if there is $\alpha \leq p-value$ there will be no reason to reject H_0. α value is 0.05 in this test. The results of the analysis of variance are presented below.

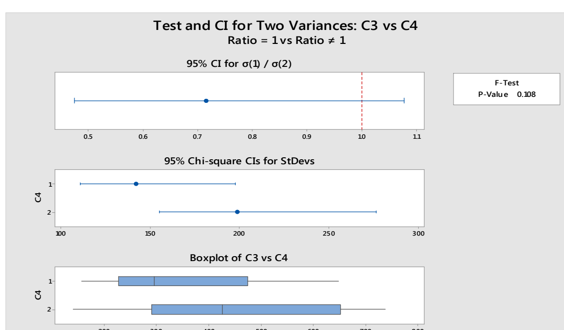

Fig. 9. Equality of variance in genetic and harmony search algorithms

Tab. 6. Analysis of variance of the MID index

Source of Changes	SS	DF	MS	F	P-value
Between groups	44278	1	44278	1.54	0.224
Within groups	840663	30	28682		
Total	904741	31			

In this section, the assumption of the equality of values versus the assumption of differences in algorithm values is examined. Given the statistical value (1.54) and the significant probability (0.224), it results that the null hypothesis must be rejected, and therefore, the difference between the two algorithms will be considerable.

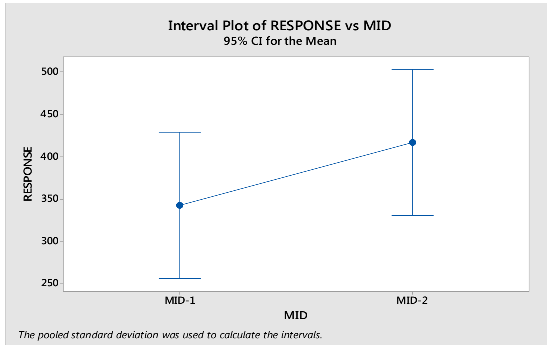

Fig. 10. Comparative graph of the MID index in the genetic and harmony search algorithms

Tab. 7. Analysis of variance of the SNS index

Source of Changes	SS	DF	MS	F	P-value
Between groups	31136	1	31136	4.3	0.047
Within groups	217432	30	7248		
Total	248567	31			

As can be seen from the results, the SNS index is $\alpha \geq p - value$, which indicates the rejection of the H_0 hypothesis. So, the difference between the algorithms is significant.

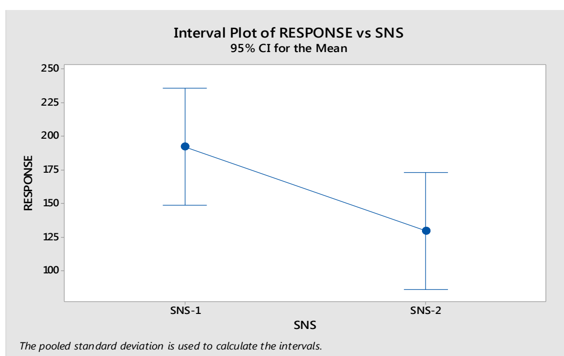

Fig. 11. Comparative graph of the SNS index in the genetic and harmony search algorithms

Tab. 8. Analysis of variance of the RAS index

Source of Changes	SS	DF	MS	F	P-value
Between groups	0.0023	1	0.00228	0	0.996
Within groups	37.1237	30	1.2374		
Total	37.1259	31			

According to the results of the analysis of variance table, there is no significant difference between the two algorithms in this index, and it is not possible to decide which algorithm performs better in this index.

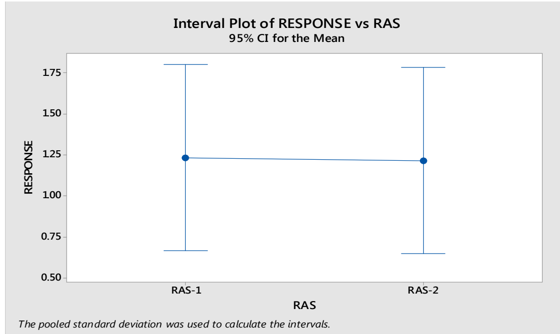

Fig. 12. Comparative graph of the RAS index in the genetic and harmony search algorithms

Based on the presented results and its analysis, it can be said that the harmony search algorithm performs better than the genetic algorithm in both SNS and MID indices.

5.5. Managerial insights

There are various indicators to prove the importance of services in today's societies. One of the most important indicators is public and private education expenses, which cover the cost of schools, universities and other educational centers. According to the information obtained by the Organization for Economic Co-operation and Development (OECD), in 2004, the countries participating in this organization spent about 6.2% of their gross domestic production (GDP) on education. This is while the amount of money spent on care and health was on average 8.9% of the GDP of these countries [2]. As one of the members of the OECD organization, the USA has spent about 1.2 trillion dollars (about 16% of GDP) for the healthcare industry in 2006, which was predicted to be 1.4 trillion dollars in 2016, that is, about 19.6 percent of this country's GDP [3]. The share of medical and health expenses in the GDP is lower than in developing countries, and this shows that the importance of the health of human resources in society increases with the level of development of the countries.

Considering the limited government resources and the increasing population, in the near future, health and treatment managers will face a lack of resources [39]. Therefore, it seems necessary to use appropriate tools for the optimal use of resources. Hospitals are one of the most important sectors of health and treatment, which account for more than 36% of government expenses [4]. Also, operating rooms, as the most important department of this center, account for 40% of the hospital's cost [5]. For this purpose, using effective techniques to reduce costs and increase resource efficiency in this center will have a significant effect on the efficiency of the entire hospital and, accordingly, the total government expenses. In this regard, in this research, by modeling the problem in the form of a chance-constrained programming approach, it was tried to obtain an optimal solution for it in small dimensions. Also, considering the limitations of this method in solving real-world problems, one of the most effective methods [40], namely the Harmony Search algorithm, was used to solve problems in medium and large dimensions. The results of comparing the proposed algorithm with the competing algorithm showed that the Harmony Search algorithm was able to achieve better quality results. The remarkable point in using the results of this research was that with the increase in the dimensions of the samples, the proposed algorithm still gave good results.

One of the main applications of these research is in the management of health systems, especially in hospitals and operating rooms, which has always been the concern of managers due to the limited resources in this field [41]. In fact, the practical purpose of this research is to help hospitals to manage and plan operating room processes more precisely, such as patient admission, and surgery scheduling in order to minimize the time of completion of the operation in the operating room, as well as the waiting time of patients, or in other words, to maximize the number of surgeries and, as a result, more regular responses to patients in the operating room.

6. Conclusion

In this study, the reduction of patients' waiting time and hospital costs along with maximizing the number of surgeries were considered as the objective function in the scheduling of operating rooms. Because the problem under consideration is Np-Hard, it is necessary to provide a solution that can solve the problem as quickly as possible with reasonable accuracy. Due to the uncertainty in the time of surgery, this model uses chance-constraint programming to model the problem. The purpose of the above method is to bring the model results closer to the real-world results. The mathematical model was solved in small-size test problems by GAMS software and in large-sizes by harmony search and genetic search algorithms. The *Lp*-metric method was used to convert the multi-objective problem to the single-objective problem, and the algorithm parameter tuning was performed by the Taguchi method. Finally, by evaluating the three indices of RAS, SNS, and MID and performing an analysis of the variance concerning the obtained values, the efficiency of the harmony search algorithm compared to the genetic algorithm was proved. According to statistical analysis in different sizes, the presented harmony search algorithm showed better performance than the genetic algorithm. To pursue further research, many cases may be considered in this research that some of which include implementing research methodology on a case study in the operating room department, and presenting a surgical operations scheduling model considering the unexpected arrival of emergency patients.

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