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RESEARCH PAPER

A fuzzy Multi-Objective Model for Surgical Staff Considering Frequency and Fairness in Time Allocation: A Case Study

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Abstract

Nurses' scheduling problems have attracted a significant amount of healthcare research, indicating the importance of these issues. In this paper, it has tried to present a multi-objective model for the assignment of nurses and anesthesiologists to surgical teams, considering frequency and fairness in allocating time to staff members. Since idle time is inevitable, we seek to divide idle time equally among staff. In addition, the break time of each staff member have an almost regular frequency during the shift. Minimizing overtime costs and maximizing attention to the willingness of surgical staff members to work overtime are other objectives of the problem. Three metaheuristic algorithms NSGA-II, MOPSO, and SPEA-II used to solve the presented model. A hybrid multi-objective genetic algorithm based on variable neighborhood search is also presented. The comparison of the solutions of 4 algorithms shows that the proposed hybrid algorithm has a significant superiority compared to other algorithms in terms of the average value of the solution, the quality of the Pareto solution set, and execution time. The presented model is compared with the real data of the surgical department of elective patients of a government hospital in Qazvin province. The obtained results show that the presented model has significantly created equality in the amount of working time of nurses and anesthesiologists in the elective surgery department. It has also spread the idle time of each staff member during the work shift, which has caused different time breaks for each one.

Keywords:
Break Time Frequency, Fuzzy Time Duration, Heuristic Algorithm, Idle Time Fairness, Nurse Scheduling

Introduction

Optimal and efficient use of hospital resources has always been one of the concerns and goals of health service managers. In the meantime, the issue of the Nurse Scheduling Problem (NSP) has included a significant amount of research in this field. Since nurses are the largest group of human resources in healthcare worldwide (Riklikienė et al., 2020) and constitute 40% of the health systems staff members (Khairunnisa et al., 2021), they play an essential role in improving the quality of care and health of patients, promoting mental and social health, and health

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education (Salvage and White, 2020). The background of researchers in this field goes back more than 50 years ago. At that time, even though computers were in their infancy, the benefits of eliminating manual work and replacing it with automation were significant, and its effectiveness in improving the healthcare delivery was evident (Strandmark et al., 2020). To have an efficient health system, it is necessary to supply human and non-human resources, especially doctors and nurses, in a correct and balanced way. The lack of personnel causes poor service to patients, and the excess of personnel also leads to an increase in the cost of the health system (Scheffler and Arnold, 2019).

By reviewing the literature on the subject, it can be seen that in general, health service systems around the world have always faced a shortage of nurses in recent decades (Buchan et al., 2015; Mrayyan and Hamaideh, 2009; Chan et al., 2013; Chiaramonte and Chiaramonte, 2008) and in many countries, this issue is the biggest challenge facing the healthcare sector (Buchan and Aiken, 2008). For this reason, every nurse has to deal with a high workload and pressure (Aiken et al., 2002). In the long term, this issue can have adverse psychological effects on nurses, which sometimes makes them decide to leave their jobs (Coomber and Barriball, 2007). Before the start of the COVID-19 pandemic, the World Health Organization announced that 6 million more nurses were needed worldwide (Bialous and Baltzell, 2020) and by 2035 this number would increase to more than 12 million (Buchan et al., 2015). Therefore, hospital managers are looking for solutions to maximize the use of available capacity and resources. The lack of nurses in healthcare service centers challenges the quality of providing services to patients and this harms the health and safety of patients (Lim et al., 2016; Chiaramonte and Chiaramonte, 2008). This issue, along with other factors such as working hours, authority support, salary, and social support, causes hospital personnel burnout (Hunsaker et al., 2015). For example, according to the surveys, more than a quarter of nurses suffer from burnout (Adriaenssens et al., 2015). Fatigue in the work environment is one of the common health problems of employees in different departments. In laborious jobs, the length of rest and its frequency during the work shift has a direct relationship with reducing fatigue and increasing job quality. Also, the lack of rest time can cause irreparable risks for the personnel and the work environment and people related to the work environment. (Fan and Smith, 2019; Sagherian et al., 2022). The existence of rest time can be a strategy against possible problems that the personnel will face in the future. Also, the experiences people gain during their breaks can have a positive effect on their job performance (Escaffi Schwarz, 2021). Many managers may consider the existence of break time as delaying work and wasting resources and time, but creating breaks for employees creates an excellent opportunity to have a snack, drink coffee, use the toilet, and talk among colleagues (Fritz et al., 2011). In some jobs, allocating rest time for employees requires a complete and temporary stop of work. In such a situation, researchers must justify the positive effect of the presence of rest time for employees to recover mental resources and energy during fatigue (Escaffi Schwarz, 2021). But this is different for nurses. Because due to the imbalance between human and non-human resources, the idleness of some of these resources is unavoidable at certain times. Meanwhile, the nursing job is one of the jobs that are both physically and mentally tough job (Min et al., 2019). It is imperative to create work breaks for nurses and hospital staff, and especially for the staff of the surgery department (Luger et al., 2023). Nurses' fatigue can cause many problems for patients. So far, many studies have been conducted about measuring the performance of nurses and hospital personnel and estimating their job satisfaction. In some of these studies, the frequency of rest time during the work shift has been proposed as one of the measuring indicators (Díaz-Alonso et al., 2022; Van Dyck, 2021; Kaur and Gujral, 2017).

Although most health systems and medical centers are facing a shortage of labor, especially a shortage of nurses, the idleness of some of the human and non-human resources of these centers is unavoidable at times. For this reason, in many researches conducted in this field, the issue of nurses’ idle time has been mentioned and its minimization has been investigated as a main goal of the model (Yilmaz, 2012; Montazeri et al., 2021; Lim et al., 2012; Srinivas and Ravindran, 2020). Of course, in different papers, the rate of nurses’ idle time is different, and its amount in hospitals of different countries has been obtained as equal to 11 percent, 15 percent, 33 percent, etc. (Wu et al., 2021; Mustaffa et al., 2022; Ajami et al., 2012). In addition, defining rest time and its duration for some jobs, such as nurses, requires specialized knowledge related to that field (Lyubykh et al., 2022).

Although the merits of employee rest periods have been proven for researchers, it is not possible to define an exact program as the optimal employee rest program, and the results of various research regarding the number, length, and time of day to determine employee rest periods are sometimes in conflict with each other (Tucker, 2003). However, a strong hypothesis about this issue is that several short rest periods are better than one or two long rest periods (Escaffi Schwarz, 2021). Because long hours reduce the performance of employees (Lim et al., 2016).

The existence of emotions and perceptions in humans has made it essential to pay attention to justice and fairness in allocating work to humans (Wolbeck, 2019). While in different fields, in personnel planning, to create a fair system, working times are divided equally and fairly among employees, but in the studies of nurse planning, only the idle time and the balance in the allocation of shifts have been paid attention to, and not much attention has been paid to its details, which can lead to an increase in job satisfaction of nurses. While the higher level of job satisfaction of the healthcare staff members and treatment services units leads to an increase in the quality of healthcare and subsequently the satisfaction of patients and clients (Welp et al., 2015). Paying attention to nurses' workload is a vital point and the imbalance in the workload causes job dissatisfaction and subsequent burnout (Nurmine, 2022) and this matter directly affects the way of planning and treating patients (Walton, 2021). Therefore, managers of hospitals and healthcare departments must consider justice between nurses by assuming equal rest time (Liu et al., 2022). For this reason, in this paper, a multi-objective model of surgical staff members' allocation to surgery is presented to manage the unavoidable idle time of surgical team members. Considering the fairness in the amount of work time allocated to each staff member is one of the innovative aims of the mathematical model presented in this paper. In addition, in our model, we addressed the fact that the idle times of each staff member are not continuous as possible and are equally divided between the surgeries assigned to those staff members. In addition, minimizing the cost of overtime, and maximizing attention to the willingness of surgical staff members to work overtime, have been considered as other goals of the model. The planning strategy is based on the block strategy, and the surgery time is considered uncertain and fuzzy.

The continuation of the paper is written as follows. In Section 2, a review of the literature on the subject is done, and some papers related to the topic are introduced. In Section 3, the assumptions of the problem and the mathematical model are presented. The presented model has four objectives. The second and third objective functions are among the most widely used in similar papers in this field. But the first and fourth objective functions are the innovative aspects of the proposed model, and their goal is to organize the unavoidable idle time of the surgical staff members. The presented model is based on the information and data collected by the surgery department of Razi Social Security Hospital in Qazvin province, and based on that, a 7-hour shift has been considered for elective surgeries. In addition to the surgeon, each surgical team includes an anesthesiologist, a scrub nurse, and one or two circulator nurses. Also, the planning horizon is weekly and the schedule for each week is set at the beginning of the previous week. In Section 4, three metaheuristic algorithms and a hybrid heuristic algorithm are introduced and compared with each other with specific metrics. In Section 5, the results of solving the problem with the mentioned algorithms are compared with the actual values, and the improvement of the data is shown. Finally, the conclusion is presented in Section 6.

Literature Review

In this section, the literature related to the nurses' scheduling and planning of the surgical team is reviewed. The problem of planning nurses in the past decades has always been the focus of those in charge of planning in healthcare. The first papers of which date back to the 1970s. The importance of this field has led many researchers in recent years to model these problems and provide methods to solve this problem (Ceschia et al., 2019).

To date, many literature review studies have been presented to review scholarly papers and writings on the subject of scheduling, assignment, and planning of nurses (McDermid et al., 2020; Li et al., 2022; Adynski et al., 2022; Gifkins et al., 2020). Despite the wide range of objectives, constraints, and solution methods presented by researchers in this field, our focus in the literature review section is only on the papers most closely related to our proposed model and solution. Thus, the emphasis is on papers that address nurses' willingness, rest breaks frequency, overtime costs, and work-time balance.

In the study of Wu et al. (2021), which investigated and compared two online and traditional scheduling systems, the nurses' idle time in each shift was found to be 72 minutes on average. However, the nurses' idle time has been significant in the paper of Ajami et al. (2012). In some departments of hospitals, some nurses' idle time reaches 33% of the duration of the work shift. Mustaffa et al., (2022) estimated the nurses' idle time to be 11.8% of the working shift hours. Lim et al. (2012) presented a goal programming model with the objective of cost minimization, idle time minimization, and personnel preference maximization. In addition to the studies mentioned above, by reviewing similar papers and studies, it can be understood that the nurses' idle time and hospital staff members have a lot to do with the nature of the hospital's activity and the tasks defined for the staff and nurses. But the clear point is that despite the efforts made by researchers to minimize the idle time of employees, this time is not equal to zero and exists more or less in all hospitals. As far as we know, no model has been mentioned about creating frequency for rest times during the shift.

One of the other goals that have been considered in the literature is the discussion of the workload of nurses and balancing the working hours of nurses. For example, Riklikienė et al (2020) investigated the relationship between the workload of ICU nurses and the quality of services and length of stay of patients in hospitals. Khairunnisa et al. (2021) and Walton (2021) conducted a regression analysis to investigate whether there is a significant relationship between nurses' workload balance and their performance. Wang et al. (2017) found that it is possible to balance the workload among nurses by shifting and changing the way patients are allocated. Topaloglu (2009) presented a model allocating hospital staff members, in which the assignment of personnel was done based on the amount of their work experience, and the workload was balanced among the personnel. Azaiez and Al-Sharif (2005) considered the issue of creating equity among hospital staff members, taking into account night shift and weekend and workload considerations. For this purpose, they minimized the deviation from the average of each personnel compared to the balanced program. In a literature review, Fishbein et al. (2019) analyzed the factors affecting workload and the effectiveness of each of them. Zhu et al. (2019) focused on the point that in some hospitals, nurses in different departments have unequal workloads. they focused on nurses' workload balance when scheduling patients. Considering that patient safety is related to various factors associated with the working conditions of nurses, Swiger et al. (2016) provided an analysis of the definition of nurses' workload in the work environment. Tsai and Li (2009) and Valouxis et al. (2012) in their research presented a two-stage strategy for nurses' planning, in which first, the nurses are assigned to shifts and working hours, and then the duties of nurses are determined. The issue of creating balance in the daily work plan of nurses is the main objective of the model presented by Topaloglu and Selim (2010), in which the number of patients and requests for nurses' leave are considered uncertain, and fuzzy. In our study, we presented workload balancing in a new way. In such a way that we balance the length of time that the surgical team personnel are working without considering the idle times between surgeries as much as possible.

By reviewing the comprehensive literature on this subject, it can be seen that despite the researchers' attention to the issue of nurses' fatigue and rest, mathematical models for these subjects have been presented in only a few papers. Martin (2015) investigated the relationship between the length of work shifts and nurses' fatigue. In their study, the length of work shifts was changed to different values in one month, and the levels of fatigue related to each change were calculated and evaluated. Klyve et al. (2022) presented a scheduling model for nurses that minimizes the amount of staff members' fatigue by considering sleep and rest times. To solve the model, they presented a combined algorithm of Constraint Programming and Large Neighborhood Search. Amindoust et al. (2021) provided a model for selecting nurses considering their fatigue and developed a hybrid algorithm to solve their model. They presented their model for a hospital in Iran and nurses in the wards of hospitalized patients with COVID-19.

The other goal that has been explored in a wide range of papers is the issue of nurses' overwork. This includes how nurses are arranged and how to minimize the cost of nurses' overtime. For example, Bard and Purnomo (2005) raised the issue of compensating for the shortage of nurses in the next 24 hours, by employing floating nurses or employing regular nurses for each shift during overtime hours. Also, Bagheri et al. (2016) presented a stochastic model in which the cost of allocation and overtime of nurses was minimized using the sample average approximation approach and considering uncertainty in the activity time and demand parameters. In addition to the above, Minimizing the cost of overtime has been used in several other studies and papers as one of the objective functions of the problem (Tan and Sun, 2016; Adynski et al., 2022; El Adoly et al., 2018).

In some articles in this field, the preferences of surgical personnel and nurses have been paid attention to. Research by Warner (1976) and Jaumard et al. (1998) were almost the first to look at nurses' work preferences. Nurses 'rankings, workload, rotation work, and nurses' leave were the issues that were addressed in these two studies. Martinelly and Meskens (2014) and (2017) considered the layout of the surgical team, taking into account the differences in the skills of scrubs so that idle time is minimized and paying attention to the willingness of a nurse to cooperate with other nurses or surgeons to the maximum. Khalili et al. (2020) presented a paper in which the scheduling of nurses' work shifts was considered by considering their work preferences and priorities in their assignment, to reduce nurses' fatigue in work shifts. They used two metaheuristic algorithms to solve the proposed model. Senbel (2021) presented a three-step heuristic approach to nurse scheduling problems in which a schedule is provided regardless of nurses. Then, attention is paid to the nurses and their preferences, and finally, the constraints related to the nurses' shifts are met.

A literature review shows that the methods for solving models in this field are comprehensive and include different approaches of solving. But our focus is on heuristic methods based on neighborhood search and metaheuristics. The variable neighborhood search method is usually used in combination with metaheuristic algorithms. For example, Abdelghany et al. (2021) presented a hybrid approach of variable neighborhood search scheduling for nurse scheduling problems. Valouxis and Housos (2000) Developed a model for assigning work shifts to nurses using a hybrid method of research strengths in operations and artificial intelligence, first estimating a linear integer programming model and then locally improving the solutions. Zhang et al. (2011) Proposed a hybrid density-based algorithm derived from the Genetic algorithm and the neighborhood search algorithm for the nurses' scheduling problem, in which some valid solutions are generated by the GA algorithm and then improved with neighborhood search variables.

Based on Table 1, in the scheduling problems of nurses, maximizing willingness to work overtime is one of the goals that has been less addressed. In contrast more attention has been paid to the desire to work on weekends. Also, the issue of fairness in the working times of staff members is one of the issues that has received less attention, and most of the research that has dealt with the issue of fairness in working hours has considered the time of staff members in the hospital. The review of previous studies shows that contrary to operating room scheduling problems, less attention has been paid to uncertainty in parameters in the nurses' and medical center staff members' scheduling problems.

Healthcare system staff fatigue is either caused by a high workload or caused by stress-causing factors and being busy with patients (Ondrejková and Halamová, 2022). In the meantime, the management of the workload of staff members has more or less received the attention of researchers in this field. The paper by Gupta et al. (2019) is one of the most comprehensiveliterature review papers on staff members' breaks. Their research showed that due to the lack of proper break times for staff, their dissatisfaction and fatigue are intensified. For example, at lunchtime, they have to eat more than they want or have the stress of doing the next activity at the same time as lunch. In addition, many staff members want to take small snack breaks during their shifts. Some of them are also unhappy that they have no time to socialize with their colleagues during their shifts. Also, some studies, such as Al-Hussami et al. (2014) and Darwad et al. (2015) show that job fatigue has a significant relationship with the decision to leave work. Therefore, in general, in different areas, the issue of the non-existence of break times or the irregularity of break times of staff members has been raised, but despite considerable attention to it, there are still many research gaps in this field. In this research, the discussion of replacing many and as many equal break times as possible, instead of few and unequal times, is considered a new aspect of innovation, and based on our knowledge, this has not been mentioned in any research.

According to the papers reviewed, the most essential features that distinguish this paper from the existing papers in this field are:

- Fair division of working times (In most previous studies, the total time of staff members' presence in the hospital has been considered, but we have only considered the working times in the surgical team.)
- Considering multiple rest times for each staff member and equally distributing these times among different surgeries for staff
- Proposing an improved hybrid algorithm of non-dominated sorting genetic algorithm, based on the neighborhood search method and comparing its results with three metaheuristic algorithms, based on the real data of a research study.
- Simultaneous consideration of scrub and circulator nurses and anesthesiologists in the surgical teams at the same time
- Attention to the different sizes of surgical teams
- Validation of model results through a real case study

Problem description

As mentioned in the introduction section, this paper considers a multi-objective model for the efficient arrangement of surgical staff. The presented objectives and constraints of the mathematical model are all defined based on the framework of Razi Hospital located in Qazvin. The hospital has two separate operating theaters for elective and non-elective patients. The surgical ward of non-elective patients, accepts these patients 24 hours a day in 3 shifts.

Table 1: An overview of some related papers

Research	Planning horizon	Staff members	Multi-objective	Objective Functions										Solution Method	Uncertainty
				willingness to overtime	Preferences to work on weekends	Preferences for the affinity of cooperation	Fairness in total workload	Fatigue	Work in consecutive shifts	Idleness in consecutive shifts	Waiting time	Overtime cost	Others		
Valouxis and Housos (2000)	1 month	Nurse								✓				Local search Tabu search	
Bard and Purnomo (2005)	1 day	Nurse	✓									✓		0-1 integer programming model	
Azaiez and Sharif (2005)	30 days	Nurse	✓	✓						✓			Minimizing the number of nurses employed	0-1 linear goal program	
Topaloglu, (2009)	30 days	Nurse	✓		✓								Considering the age of employees	Weighted method	
Tsai and Li (2009)		Nurse											Minimizing idle time	GA	
Topaloglu and Selim (2010)	2 weeks	Nurse	✓							✓			Considering work shift preferences	Heuristic	Fuzzy
Valouxis et al. (2012)	1 week	Nurse								✓				Two-stage heuristic	
Martinelly and Meskens (2014)	1 day	Nurse	✓			✓					✓			ε-Constraint	
Tan and Sun (2016)		Nurse											Minimizing the personnel cost	Heuristic	
Bagheri at al. (2016)	1 day	Nurse										✓		SAA	Stochastic
Martinelly and Meskens (2017)	1 week	Scrub and Circulator nurses	✓			✓					✓			ε-Constraint Heuristic	
Wang (2017)	1 month	Nurse							✓					Monte Carlo simulation Dynamic programming	Stochastic
El Adoly et al. (2018)	1 week	Nurse Head nurses	✓									✓	Minimizing the head nurses' costs	Heuristic	
Hamid et al. (2020a)		Nurse	✓											NSGA-II & MOPSO & MOTS	
Khalili et al. (2020)	1 week	Nurse	✓					✓	✓					NSGA-II & MOPSO & Topsis	
Strandmark et al. (2020)	1 week	Nurse	✓		✓				✓				Minimizing the number of unfulfilled shifts	Heuristic (Column generation)	
Yousefi Nejad Attari et al. (2020)	1 day	Emergency staff	✓		✓							✓	Minimizing service delivery time	Simulation with Arena software	
Hamid et al. (20۲۰b)		Nurse anesthesiologist											Minimizes the makespan		
Sharifi et al. (2021)	1 month	Nurse	✓											NSGA-II Bees	
Pahlevanzadeh et al. (2021)		Nurse	✓						✓				Maximizing nurses' shift and cooperation preferences	Fuzzy Topsis Stakelberg & Nash	
Amindoust et al. (2021)	1 day	Nurse	✓					✓					Minimizing hospital costs	Heuristic & GA	
Klyve et al. (2022)		Nurse						✓						VNS & constraint programming	
Guo and Bard (2022)	1 month	Nurse	✓					✓		✓				Column generation	
Nguyen (2022)	1 day	Types of healthcare staff					✓							Heuristic	Robust
Nobil et al. (2022)	Multi-day	Nurse										✓		LP	
This study	1 week	Scrub nurses Circulator nurses anesthesiologist	✓	✓			✓					✓	Time breaks between assigned surgeries	NSGA-II SPEA-II MOPSO NSGAVNS (hybrid)	Fuzzy

However, the elective patient ward, which includes outpatients and non-emergency patients, operates in only one shift for a maximum of 9 hours. The number of nurses in each department is fixed. But Patients are different, and they rotate between the two parts. Of course, if desired, each nurse can work only in the ward of elective patients, in which case they have to attend six working days a week. In contrast, nurses in the surgical ward of non-elective patients have the advantage of a variety of shifts and can have more than one day off per week. To better understand the problem and proposed model, before introducing sets, parameters, variables, and mathematical models, the assumptions of the model are defined based on a case study:

- All patients are pre-planned, and no accidental patient enters the surgical ward (Only elective patients are considered).
- Each surgery continues without interruption until the end.
- There are limited human resources in the surgical ward.
- Any surgeon, anesthesiologist, and nurse can only be part of a surgical team at any one time.
- Adequate recovery beds are available to prevent planning disruption.
- The planning horizon is limited to *d* days. (For our case study, a week with 6 working days is considered.)
- Every working day includes a ٧-hour shift and 2 hours of overtime (7:30 to 1٤:30 & 1٤:30 to 16:30).
- Patients are scheduled for that day, assuming they are ready for surgery.
- Each surgical team consists of one surgeon, anesthesiologist, scrub nurse, and one or more circulator nurses.
- The availability of nurses during a work shift is not necessarily the same (Daily and hourly leave).
- Nurses' salaries are different and unequal based on their level of education and work experience.
- Overtime is limited for each nurse.

Mathematical Model

The notations including sets, parameters, and decision variables:

Table 2: Sets, parameters, and variables

Sets		
o	index of an operation	$o \in \{1,2,\ldots,O\}$
t	index of a time slot	$t \in \{1,2,\ldots,T\}$
d	index of a day	$d \in \{1,2,\ldots,D\}$
r	index of an operating room	$r \in \{1,2,\ldots,R\}$
s	index of a surgeon	$s \in \{1,2,\ldots,S\}$
a	index of an anesthesiologist	$a \in \{1,2,\ldots,A\}$
n	index of a scrub nurse	$n \in \{1,2,\ldots,N\}$
h	index of a circulator nurse	$h \in \{1,2,\ldots,H\}$

Parameters	
du_o	Duration of operation o
DFN_n	Limit of overtime for scrub *n* in time horizon
DFH_h	Limit of overtime for circulator *h* in time horizon
DFA_a	Limit of overtime for anesthesiologist *a* in time horizon
M^{s}_{std}	Binary parameter. It is equal to 1 if the surgeon *s* is available at time *t* on day *d*. Else equal 0
M^{a}_{atd}	Binary parameter. It is equal to 1 if the anesthesiologist *a* is available at time *t* on day *d*. Else equal 0
M^{n}_{ntd}	Binary parameter. It is equal to 1 if the scrub nurse *n* is available at time *t* on day *d*. Else equal 0
M^{h}_{htd}	Binary parameter. It is equal to 1 if the circulator nurse *h* is available at time *t* on day *d*. Else equal 0

ca_a	Overtime cost of scrub anesthesiologist *a* per a time
cn_n	Overtime cost of scrub nurse *n* per a time
ch_h	Overtime cost of circulator nurse *h* per a time
m_o^h	Number of circulator nurses needed for operation *o*
0_s	Set of surgeries assigned to the surgeon *s* $(o_s \in O)$
w_{atd}^a	Tendency to overtime work for anesthesiologist *a* on time *t* in day *d*
w_{ntd}^n	Tendency to overtime work for scrub nurse *n* on time *t* in day *d*
w_{htd}^h	Tendency to overtime work for circulator nurse *h* on time *t* in day *d*

Variables

xo_{otdr}	Binary variable. Equals 1 if the operation *o* perform at time *t* on day *d* in room *r*. Else equals 0
xo_{otdr}^{start}	Binary variable. Equals 1 if the operation *o* starts at time *t* on day *d* in room *r*. Else equals 0
xi_{itdr}	Binary variable. Equals 1 if surgeon/personnel *i* work in time *t* on day *d* in room *r*. Else equals 0
xi_{itdr}^{start}	Binary variable. Equals 1 if personnel i starts work in a surgical team at time *t* on day *d* in room *r*. Else equals 0.
xi_{itdr}^{finish}	Binary variable. Equals 1 if personnel i finishes work in a surgical team at time *t* on day *d* in room *r*. Else equals 0.
η_{itd}^i	The length of idle time of the personnel i , from time slot *t* to the first start of work on day *d*
ψ_{id}^i	The ideal idle time between two consecutive surgeries for personnel i on day *d*
φ_{itd}^i	Binary variable. Equals 1 if personnel i terminates his/her work in a surgical team at time slot t of day d. Else equals to 0
τ_{itd}^i	Binary variable. Equals 1 if personnel i starts working in at least one new surgical team from time slot t to the end of the shift on day d. Else equals to 0

Constraints

The mathematical model presented in this paper is an extension of the model developed by Meskens et al. (2013). In this model, in the first stage, surgeries should be assigned to the available time slots. Then in the second stage, surgical staff members are assigned to surgical teams due to their availability at the times assigned to surgeries. In the first stage, each surgery should be performed only once, consecutively and without interruption, and only if the surgeon is available. Constraints (1) to (8) are the constraints of step 1.

$$\sum_{o=1}^{O} xo_{otdr} \leq 1 \qquad \forall t,d,r \tag{1}$$

$$\sum_{t=1}^{T}\sum_{d=1}^{D}\sum_{r=1}^{R} xo_{otdr} = du_o \qquad \forall o \tag{2}$$

$$\sum_{t=1}^{T}\sum_{d=1}^{D}\sum_{r=1}^{R} {xo^{start}}_{otdr} = 1 \qquad \forall o \tag{3}$$

$$\sum_{t=1}^{T}\sum_{d=1}^{D}\sum_{r=1}^{R} {xo^{finish}}_{otdr} = 1 \qquad \forall o \tag{4}$$

$$xo_{otdr} = \sum_{\tau=\max(1,t-du_o+1)}^{t} {xo^{start}}_{o\tau dr} \qquad \forall o,t,d,r \tag{5}$$

$${xo^{finish}}_{o(t+du_o-1)dr} = xo_{otdr}^{start} \qquad \forall t \in \{1,...,\mathrm{T}-du_o+1\}, o,d,r \tag{6}$$

$$\sum_{o \in O_s} xo_{otdr} \leq M_{std}^S \qquad \forall s,t,d,r \tag{7}$$

$$xs_{stdr} = \sum_{o \in O_s} xo_{otdr} \qquad \forall s,t,d,r \tag{8}$$

Constraint (1) ensures that there is a maximum of one surgery possible at any time of the day, in any operating room, and constraint (2) shows the duration of each surgery. Constraints (3) and (4) indicate that each surgery starts only once and ends once. Constraints (5) and (6) indicate to which time blocks each surgery is assigned. These two constraints also ensure that surgery is performed non-stop. Constraint (7) states that surgeons can only perform surgeries when they are available. Constraint (8) ensures that every surgeon is present in a maximum of one surgical team at any time of the day.

The members of the surgical team are present in the surgical team from the beginning to the end of the surgery. Each surgical team includes one scrub nurse, one or more circulator nurses, and one anesthesiologist. These assumptions are listed in constraints (9) to (17).

$$\sum_{r=1}^{R} xn_{ntdr} \le M_{ntd}^{N} \qquad \forall n,t,d \tag{9}$$

$$\sum_{s=1}^{S} xs_{stdr} = \sum_{n=1}^{N} xn_{ntdr} \qquad \forall t,d,r \tag{10}$$

$$\sum_{n=1}^{N}\sum_{d=1}^{D}\sum_{r=1}^{R}\sum_{t=1}^{T-du_o+1}\left[\frac{\sum_{\tau=t}^{t+du_o-1} xo_{o\tau dr}.xn_{n\tau dr}}{du_o}\right]=1 \qquad \forall o \tag{11}$$

$$\sum_{r=1}^{R} xa_{atdr} \le M_{atd}^{A} \qquad \forall a,t,d \tag{12}$$

$$\sum_{s=1}^{S} xs_{stdr} = \sum_{a=1}^{A} xa_{atdr} \qquad \forall t,d,r \tag{13}$$

$$\sum_{a=1}^{A}\sum_{d=1}^{D}\sum_{r=1}^{R}\sum_{t=1}^{T-du_o+1}\left[\frac{\sum_{\tau=t}^{t+du_o-1} xo_{o\tau dr}.xa_{a\tau dr}}{du_o}\right]=1 \qquad \forall o \tag{14}$$

$$\sum_{r=1}^{R} xh_{htdr} \le M_{htd}^{H} \qquad \forall h,t,d \tag{15}$$

$$\sum_{h=1}^{H} xh_{htdr} = \sum_{o=1}^{O} xo_{otdr}.m^{h}{}_{o} \qquad \forall t,d,r \tag{16}$$

$$\sum_{h=1}^{H}\sum_{d=1}^{D}\sum_{r=1}^{R}\sum_{t=1}^{T-du_o+1}\left[\frac{\sum_{\tau=t}^{t+du_o-1} xo_{o\tau dr}.xh_{h\tau dr}}{du_o}\right]=m_o^h \qquad \forall o \tag{17}$$

Constraint (9) shows that each scrub nurse, if available, can only be assigned to at most one surgery, and constraint (10) states if a surgery is assigned to a time block in a day and an operating room, a scrub nurse should be assigned to that time block in that day and that operating room. The personnel assigned to each surgery is fixed and unchanged until the end of that surgery. It means that if a nurse is assigned to a surgery, the same nurse must participate in all time slots of that surgery. This issue is guaranteed by the constraint (11). Constraints (12), (13), and (14) are similar to constraints (9), (10), and (11), except that they are for anesthesiologists instead of scrub nurses. Constraint (15) represents each circulator nurse is not assigned to more than one surgery at the same time. Constraint (16) shows how many circulators each surgery needs. Constraint (17) ensures the circulator nurses assigned to each surgery are fixed until the end of the surgery.

Constraints (18) to (20) ensure that the overtime time of each surgical staff member does not exceed the specified limit. Constraints (21) to (26) indicate in which time block, at what time slots, and in which operating room each surgical staff member began or completed his or her work on a surgical team.

$$\sum_{d=1}^{D}\sum_{r=1}^{R}\sum_{t\in T_{over}} xn_{ntdr} \le DFN_n \qquad \forall n \tag{18}$$

$$\sum_{d=1}^{D}\sum_{r=1}^{R}\sum_{t\in T_{over}} xa_{atdr} \le DFA_a \qquad \forall a \tag{19}$$

$$\sum_{d=1}^{D}\sum_{r=1}^{R}\sum_{t\in T_{over}} xh_{htdr} \le DFH_h \qquad \forall h \tag{20}$$

$$xa_{atdr}^{start} = xa_{atdr}.\sum_{o=1}^{O} xo_{otdr}^{start} \qquad \forall a,t,d,r \tag{21}$$

$$xa_{atdr}^{finish} = xa_{atdr}.\sum_{o=1}^{O} xo_{otdr}^{finish} \qquad \forall a,t,d,r \tag{22}$$

$$xn_{ntdr}^{start} = xn_{ntdr}.\sum_{o=1}^{O} xo_{otdr}^{start} \qquad \forall n,t,d,r \tag{23}$$

$$xn_{ntdr}^{finish} = xn_{ntdr}.\sum_{o=1}^{O} xo_{otdr}^{finish} \qquad \forall n,t,d,r \tag{24}$$

$$xh_{htdr}^{start} = xh_{htdr}.\sum_{o=1}^{O} xo_{otdr}^{start} \qquad \forall h,t,d,r \tag{25}$$

$$xh_{htdr}^{finish} = xh_{htdr}.\sum_{o=1}^{O} xo_{otdr}^{finish} \qquad \forall h,t,d,r \tag{26}$$

Objective functions

Objective function 1

Goals of this as mentioned in section 1, one of the problem is to balance the work time assigned to members of the surgical team. This goal can be defined in the horizon of one, two, or more days. Therefore, the objective function equation (27) applies this flexibility to the d-day time horizon. For this issue first, the total surgical time of the operating room is calculated, and by dividing among all the staff members present in the operating room, the average working times of each staff member are obtained. Then the standard deviation of this average time is obtained from the times assigned to each individual. The purpose of this equation is to minimize this standard deviation.

$$\begin{aligned} min \ & \sum_{n=1}^{N}\left|\sum_{d=1}^{D}\sum_{t=1}^{T}\sum_{r=1}^{R} xn_{ntdr} - \frac{\sum_{m=1}^{N}\sum_{t=1}^{T}\sum_{d=1}^{D}\sum_{r=1}^{R} xn_{mtdr}}{N}\right| + \\ & \sum_{a=1}^{A}\left|\sum_{d=1}^{D}\sum_{t=1}^{T}\sum_{r=1}^{R} xa_{atdr} - \frac{\sum_{m=1}^{A}\sum_{t=1}^{T}\sum_{d=1}^{D}\sum_{r=1}^{R} xa_{mtdr}}{A}\right| + \\ & \sum_{h=1}^{H}\left|\sum_{d=1}^{D}\sum_{t=1}^{T}\sum_{r=1}^{R} xh_{htdr} - \frac{\sum_{m=1}^{H}\sum_{t=1}^{T}\sum_{d=1}^{D}\sum_{r=1}^{R} xh_{mtdr}}{H}\right| \end{aligned} \tag{27}$$

Objective function 2

Equation (28) is another goal of this problem, which aims to minimize the cost that management must pay for the overtime of the surgical team staff. In this objective function, the problem is looking for a kind of allocation that, firstly, does not perform surgery in the blocks after the standard work shift (at overtime time slots), and secondly, if surgery is performed in these blocks, try to hire lower paid staff.

$$min \left(\sum_{a=1}^{A} (\sum_{d=1}^{D}\sum_{r=1}^{R}\sum_{t\in T_{over}} xa_{atdr}).C_a + \sum_{n=1}^{N} (\sum_{d=1}^{D}\sum_{r=1}^{R}\sum_{t\in T_{over}} xn_{ntdr}).C_n + \sum_{h=1}^{H} (\sum_{d=1}^{D}\sum_{r=1}^{R}\sum_{t=T_{over}} xh_{htdr}).C_h \right) \tag{28}$$

Objective function 3

As mentioned before, due to the imbalance between human resources, it is not possible to make full use of surgical time and rooms. One way to reduce this is to use overtime. In the meantime, it is essential to pay attention to the desire of the surgical staff members to work overtime. The purpose of equation (۲۹) is to maximize attention to the willingness of surgical staff members to work overtime.

$$max \begin{pmatrix} \sum_{n=1}^{N}\sum_{d=1}^{D}\sum_{r=1}^{R}\sum_{t\in T_{over}} xn_{ntdr}.w^{n}_{ntd} + \\ \sum_{h=1}^{H}\sum_{d=1}^{D}\sum_{r=1}^{R}\sum_{t\in T_{over}} xh_{htdr}.w^{h}_{htd} + \\ \sum_{a=1}^{A}\sum_{d=1}^{D}\sum_{r=1}^{R}\sum_{t\in T_{over}} xa_{atdr}.w^{a}_{atd} \end{pmatrix} \tag{29}$$

Objective function 4

The fourth purpose of this paper is to balance the useful working hours of each member of the surgical staff. So if there is idle time for each staff member of the surgical team, this time should be divided and distributed among the different surgeries assigned to that staff. For each nurse or anesthesiologist, the time interval between the end of work on the surgical team and the beginning of work in another surgical team is defined as an idle time block. To better understand this objective function, we define four variables φ, τ, η, and ψ.

The η variables describe the length of the idle time until the first start of work on a new surgical team in the current shift for nurses and anesthesiologists. Constraints (30) to (32) calculate the values of these variables. So that for each member of the surgical team, the first start of work on a new surgical team after the current time is shown.

$$\eta^{a}_{atd} = \left(\min_{+} (\ T,\ (t+1).\sum_{r=1}^{R} xa^{start}_{a(t+1)dr},\ (t+2).\sum_{r=1}^{R} xa^{start}_{a(t+2)dr},\ \ldots,\ T.\sum_{r=1}^{R} xa^{start}_{aTdr}\ ) \right) \quad \forall a,t,d \tag{30}$$

$$\eta^{n}_{ntd} = \left(\min_{+} (\ T,\ (t+1).\sum_{r=1}^{R} xn^{start}_{n(t+1)dr},\ (t+2).\sum_{r=1}^{R} xn^{start}_{n(t+2)dr},\ \ldots,\ T.\sum_{r=1}^{R} xn^{start}_{nTdr}\ ) \right) \quad \forall n,t,d \tag{31}$$

$$\eta^{h}_{htd} = \left(\min_{+} (\ T,\ (t+1).\sum_{r=1}^{R} xh^{start}_{h(t+1)dr},\ (t+2).\sum_{r=1}^{R} xh^{start}_{h(t+2)dr},\ \ldots,\ T.\sum_{r=1}^{R} xh^{start}_{hTdr}\ ) \right) \quad \forall n,t,d \tag{32}$$

The ψ variables are equally dividing the daily idle time of each staff member by the number of vacancies between surgeries assigned to each staff. For example, if a nurse participates with 4 surgical teams during a shift and is idle for 2 hours, the ψ variable is equal to 40 (120/(4-1)=40 minutes).

The values obtained for this variable are considered ideal criteria, and the objective function is to minimize deviations from these criteria. Constraints (33) to (35) describe how to calculate this variable. In this paper, it is assumed that the degree of difficulty of different surgeries is the same.

$$\psi_{ad}^{a}=\frac{T-\sum_{r=1}^{R}\sum_{t=1}^{T}xa_{atdr}}{\sum_{r=1}^{R}\sum_{t=1}^{T}xa_{atdr}^{start}-1} \qquad \forall a,d \tag{33}$$

$$\psi_{nd}^{n}=\frac{T-\sum_{r=1}^{R}\sum_{t=1}^{T}xn_{ntdr}}{\sum_{r=1}^{R}\sum_{t=1}^{T}xn_{ntdr}^{start}-1} \qquad \forall n,d \tag{34}$$

$$\psi_{hd}^{h}=\frac{T-\sum_{r=1}^{R}\sum_{t=1}^{T}xh_{htdr}}{\sum_{r=1}^{R}\sum_{t=1}^{T}xh_{htdr}^{start}-1} \qquad \forall h,d \tag{35}$$

φ variables are binary variables equal to 1 if the staff member terminates the work in a surgical team. Calculating this binary variable is stated in equations (36) to (38).

$$\varphi_{atd}^{a}=\left(\sum_{r=1}^{R}xa_{atdr}^{finish}\right) \qquad \forall a,t,d \tag{36}$$

$$\varphi_{ntd}^{n}=\left(\sum_{r=1}^{R}xn_{ntdr}^{finish}\right) \qquad \forall n,t,d \tag{37}$$

$$\varphi_{htd}^{h}=\left(\sum_{r=1}^{R}xh_{htdr}^{finish}\right) \qquad \forall h,t,d \tag{38}$$

The τ variables are binary variables equal to 1 only under one condition, which is that the staff member starts working on at least one other surgery after the current time interval and on this day. Constraints (39) to (41) describe how to calculate this variable. The parameter M is a very large number and ε is a very small number close to zero.

$$\tau_{atd}^{a}=\left\lfloor\frac{M-\varepsilon+\sum_{r=1}^{R}\sum_{\tau=t+1}^{T}xa_{a\tau dr}^{start}}{M}\right\rfloor \qquad \forall a,t,d \tag{39}$$

$$\tau_{ntd}^{n}=\left\lfloor\frac{M-\varepsilon+\sum_{r=1}^{R}\sum_{\tau=t+1}^{T}xn_{n\tau dr}^{start}}{M}\right\rfloor \qquad \forall n,t,d \tag{40}$$

$$\tau_{htd}^{h}=\left\lfloor\frac{M-\varepsilon+\sum_{r=1}^{R}\sum_{\tau=t+1}^{T}xh_{h\tau dr}^{start}}{M}\right\rfloor \qquad \forall h,t,d \tag{41}$$

According equation (42), the purpose of the fourth objective function is to create a balance between the useful working hours of each member of the surgical staff. If the variables φ and τ for each personnel are *non-zero* at any time and every day, the difference between the idle time of the personnel until they start working again will be minimized from the average.

$$\min \sum_{a=1}^{A}\sum_{d=1}^{D}\sum_{t=1}^{T}\varphi_{atd}^{a}.\tau_{atd}^{a}.\left(\left(\eta_{atd}^{a}-t+1\right)-\psi_{ad}^{a}\right)^{2}+ \sum_{n=1}^{N}\sum_{d=1}^{D}\sum_{t=1}^{T}\varphi_{ntd}^{n}.\tau_{ntd}^{n}.\left(\left(\eta_{ntd}^{n}-t+1\right)-\psi_{nd}^{n}\right)^{2}+ \sum_{h=1}^{H}\sum_{d=1}^{D}\sum_{t=1}^{T}\varphi_{htd}^{h}.\tau_{htd}^{h}.\left(\left(\eta_{htd}^{h}-t+1\right)-\psi_{hd}^{h}\right)^{2} \tag{42}$$

To better understand the objective function *Z4*, a simple numerical example for a nurse is presented in Fig. 1. It is assumed that each shift (8 hours) consists of 32 time slots of 15 minutes. This nurse is present in five surgical teams, and the length of time for these 5 surgeries is equal to 5 - 4 - 4 - 3 - 5 time blocks. Therefore, this nurse must work for 21 time slots. The idle time of this nurse in this shift is equal to 11-time slots. To divide the idle time equally between the five surgeries, four time blocks should be created. For Fig. 1(a), the standard deviation of the length of idle time blocks is equal to:

$(1\text{-}2.75)^2 + (2\text{-}2.75)^2 + (0\text{-}2.75)^2 + (5\text{-}2.75)^2 + (1\text{-}2.75)^2 + (2\text{-}2.75)^2 = 19.875$

But for the optimal solution shown in Fig. 1(b), this value is equal to:

$(3\text{-}2.75)^2 + (3\text{-}2.75)^2 + (3\text{-}2.75)^2 + (2\text{-}2.75)^2 = 0.75$

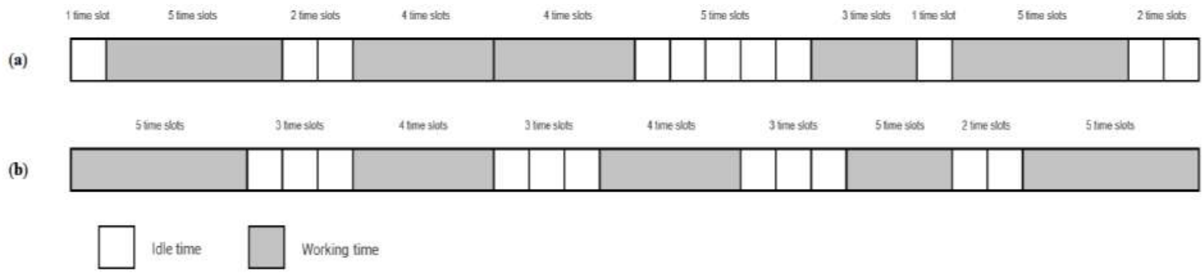


Fig.1. A numerical example to demonstrate the improvement of the solution by the objective function *Z4*

Surgeries in fuzzy time

In the studies carried out in surgical scheduling and assigning nurses to surgical procedures, surgery time is considered both certain and uncertain. But in the real world, surgery times are rarely precisely as predicted. If a confidence interval can be considered for the given data with previous experiences, this interval is a fuzzy interval, and the plausible values within this interval are fuzzy numbers (Afsar et al., 2022). The time required for each surgery is not fixed and can vary. Therefore the time parameter is uncertain, which in the literature is usually defined as probabilistic distributions or fuzzy numbers (Wang et al., 2021). In our case study, parts of the historical data related to surgery times are incomplete. Fuzzy method can better manage uncertainties caused by defects and fluctuations (Wang et al., 2022). Therefore to facilitate calculations in this paper, the use of fuzzy numbers is preferred to probabilistic models. We used fuzzy logic to convert the time parameter from indefinite to definite.

In the proposed model, the duration of surgeries is discrete. While the time of surgerym according to the information obtained from the hospital, is continuous. To convert time numbers from continuous to discrete, it is necessary to define equal blocks. If we define the duration of each continuous operation as a parameter such as dum_o, and the length of each time block as a parameter, such as L, then the number of time blocks of each discrete operation is obtained from equation (43).

$$du_o = \left[\frac{dum_o}{L}\right] + 1 \tag{43}$$

Since the Jiménez method is an interactive method and the decision maker has a good role and considerable authority in determining the degree of the severity of uncertainty, the Jiménez approach hasbeen used for this problem. Despite having a simple structure that reduces computing time, this method also has high efficiency and accuracy. Also, in this method, mutual participation of decision makers is used during the decision making process. According to the Jiménez method of ranking fuzzy numbers, triangular fuzzy numbers are divided into three numbers: optimistic, probable, and pessimistic (Jiménez et al., 2007). Each triangular fuzzy value is represented as $\tilde{\omega} = (\omega^t, \omega^q, \omega^s)$ with the values ω^t , ω^q ,and ω^s representing the pessimistic value, the expected value, and the optimistic value, respectively. Expected interval and expected value of fuzzy parameters in the Jiménez method are defined as equations (44) to (45). For both fuzzy numbers *a* and *b*, the membership function is equal to equation (46)

$$EI(\tilde{c}) = [E_1^c, E_2^c] = \left[\int_0^1 f_c^{-1}(x)dx, \int_0^1 g_c^{-1}(x)dx\right] = \left[\frac{1}{2}(c^t + c^q), \frac{1}{2}(c^q + c^s)\right] \tag{44}$$

$$EV(\tilde{c}) = \frac{E_1^c + E_2^c}{2} = \frac{c^t + 2c^q + c^s}{4} \tag{45}$$

$$\mu_M(\tilde{a}, \tilde{b}) = \begin{cases} 0 & E_2^a \le E_1^b \\ \dfrac{E_2^a - E_1^b}{E_2^a - E_1^b - (E_1^a - E_2^b)} & [E_1^a - E_2^b, E_2^a - E_1^b] \\ 1 & E_2^a \le E_1^b \end{cases} \tag{46}$$

The only uncertain parameter of the model is the surgery duration, which is considered a triangular fuzzy parameter and is defined as $\tilde{dum}_o = (dum_o^t, dum_o^q, dum_o^s)$. After de-fuzzing the parameter with the Jiménez method, equation (47) is obtained, which should replace equation (43). The objective function and other problem constraints remain unchanged, in which α is the confidence level.

$$du_o = \left[\frac{\alpha(\frac{dum_o^m + dum_o^o}{2}) + (1-\alpha)(\frac{dum_o^p + dum_o^m}{2})}{L}\right] + 1 \tag{47}$$

Solution approach

Planning problems are often NP-hard. (Duka, 2014) and to achieve near-optimal solutions in NP-hard problems, metaheuristic algorithms are used (Gomathi and Sharmila, 2014). In the present paper, to solve the proposed NSP model, we have used NSGA-II, MOPSO, and SPAE-II metaheuristic algorithms. In addition, the heuristic NSGAVNS algorithm, which is a combination of the NSGA-II and VNS algorithms, is proposed to solve this model. Before describing the proposed algorithm, it is necessary to provide a framework for multi-objective optimization problems.

Multi-objective problems

Since the presented NSP is a multi-objective optimization problem, the optimal solution is a

Pareto optimal front. Heuristic and metaheuristic algorithms based on the ranking of solutions based on non-dominated sorting of solutions introduce best Pareto front in multi-objective problems. Therefore, the optimal solutions of the first Pareto front are selected as the main solutions of the metaheuristic algorithm, and the evaluation criteria of each algorithm are based on the solutions of the first front of that algorithm (Das and Pratihar, 2019).

Pareto-Front

In any multi-objective problem with *m* a function that the sets of different solutions are in the space R^n, we can say that the α solution set dominated the β solution set ($x_\alpha \prec x_\beta$) if :

1. For each k of the set $\{1, 2, ..., m\}$: $f_k(x_\alpha) \le f_k(x_\beta)$
2. For at least one k of the set $\{1, 2, ..., m\}$: $f_k(x_\alpha) < f_k(x_\beta)$

Proposed algorithm

Decoding and Encoding the solution

In this problem, the structure of the solution is two-stage. In the first stage, surgeries are allocated to available free time, and in the second stage, available nurses and anesthesiologists are assigned to surgeries. The problem solution can be displayed in the form of chromosome strings. To show the problem solution, O number of chromosome strings with a length of 5+mh(o) of the gene is used. For example, if surgery O requires two circulator nurses, the corresponding chromosome string contains seven genes. The first three genes of the chromosome, indicate the time and place of surgery, respectively. The first, second, and third genes show the day and time of surgery and the operating room. The second three genes on the chromosome represent members of the surgical staff. The fourth, fifth, and sixth genes represent the anesthesiologist, scrub nurse, and circulator nurse assigned to surgery, respectively. If the surgery requires more than one circulator nurse, genes seven and eight, etc., are also considered. Considering that all the surgeries studied in this paper had one or two circulator nurses, therefore in this research, two genes related to the circulator nurses are considered for each surgery. If the surgery requires only one circulator nurse, no value is considered for the seventh gene.

To better understand how to decode the problem solution, an example with the following parameters is considered:

O=12, T=24, D=2, R=5, A=5, N=5, H=6

The problem solution is a matrix (5+h)*O. That is, for each patient, there are 5+h arrays that represent the time of surgery (d, r), location of surgery (r), and members assigned to the surgical team (a, n, h).

Assume that surgery number 1 requires nine time slots. The random number 0.53 corresponds to d, which means the number of days of surgery number 1. This random number indicates that the surgery will be performed on the second day ([0.53*2]+1=2).

Also, the number 0.09 shows the starting time of surgery number 1, which is equal to block number 3 ([0.09*24]+1=3).

This means this surgery occupies 3 to 11 blocks of the second day. If we assume that the other random numbers are according to Fig.2, then the other variables of the first surgery are equal to:

o=1, t=3, d=2, r=4, a=3, n=4, h_1=3, (h_2=3 if needed)

The variables of other surgeries are determined similarly.

If another surgery is performed on $t=3$, $d=2$, due to the time overlap of this surgery with surgery number 1, room number 3 is occupied, and rooms 1, 2, 4, and 5 are available. Therefore, this surgery is assigned to room number 5

([0.76*4]+1=4 The fourth available room is number 5).

	o_1	o_2	o_3	o_4	o_5	o_6	o_7	o_8	o_9	o_{10}
t	0.09	0.67	0.41	0.10	0.10	0.18	0.05	0.15	0.55	0.02
d	0.53	0.22	0.75	0.17	0.04	0.12	0.22	0.55	0.06	0.01
r	0.76	0.25	0.34	0.95	0.17	0.61	0.24	0.22	0.35	0.59
a	0.54	0.57	0.49	0.28	0.82	0.93	0.05	0.22	0.99	0.41
n	0.70	0.66	0.26	0.31	0.36	0.28	0.13	0.92	0.93	0.76
h_1	0.46	0.69	0.44	0.08	0.57	0.23	0.27	0.23	0.21	0.14
h_2	0.06	0.35	0.59	0.26	0.04	0.61	0.27	0.29	0.14	0.48

Fig.2. Schematic of the problem solutions with random numbers

NSGA-II

NSGA-II is a simple yet powerful evolutionary algorithm with non-dominate sorting and crowding distance features for solving multi-objective problems, which were first introduced by Deb (2001). NSGA-II starts with random solutions and develops those solutions, and then the developed solutions are evaluated in each iteration of the algorithm.

Crossover

In the genetic algorithm, new chromosomes are produced with the crossover operator. After the generation of new chromosomes, the best chromosomes created remain in the competition, to pass the best characteristics of the previous generation to the next generations. In the proposed algorithm, a two-point-cut crossover is used for the solution. Fig.3 shows the schematic structure of the chromosome for solutions and the generation of two new solutions.

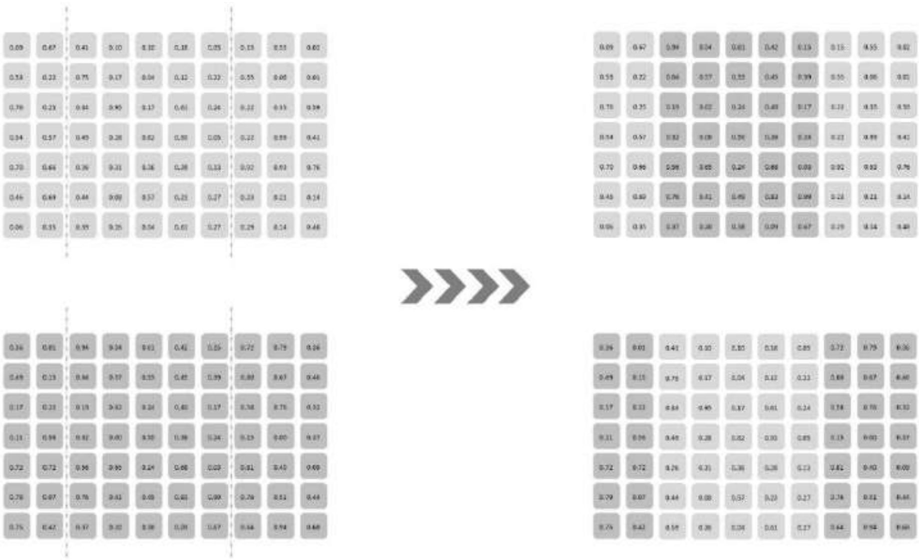


Fig.3. A two-point crossover

Mutation

The mutation operator prevents the solution from getting stuck in the local optimum. There are various structures available for this operator. For this model, three structures Exchange, Insertion, and Reversion, are used, which are schematically shown in Fig. 4-6.

Fig. 4. Example of an exchange mutation

Fig. 5. Example of an insertion mutation

Fig. 6. Example of an inversion mutation

VNS

Although the proposed metaheuristic methods provide very good solutions for the problem of allocation and scheduling of the surgical staff, using a neighborhood search algorithm can prevent the solutions from remaining fixed in the local optimum, which improves the solution and solves the problem faster because different metaheuristic algorithms have a relatively long solution time for the proposed model. The VNS algorithm was first proposed by Mladenović and Hansen (1997), which significantly contributed to solving global problems in various heuristics and metaheuristics. Compared to other metaheuristic algorithms, the VNS algorithm is simpler and less complex (Kong et al., 2021). There is usually a direct relationship between the size of the problem and the probability of the solution being compromised in the local optimal region. VNS algorithm, unlike various metaheuristic algorithms such as genetic and PSO, does not pursue a specific path. Instead, during the process, by systematically changing the location of the solutions (based on the structures defined for the problem), it escapes from being in the local optimum. The VNS algorithm starts with an initial solution. Then with the help of neighborhood structures designed for the problem in question, the initial solution is continuously improved until the termination condition is reached. For the initial solution of this algorithm, the solutions of other heuristic and metaheuristic algorithms can be used, or a random initial solution can be used. The main basis of this algorithm is local search and shaking operators, and for neighboring structures, a certain number of superior structures are often selected by designing different structures and by trial and error and checking the improvements of each structure.

Proposed NSGAVNS

As explained in section 4.3, solution chromosomes contain two sets of genes. The first set includes genes related to the time (day and hour) and place (operating room) of surgeries. The second set of genes on the solution chromosome includes anesthesiologists and scrub and circulator nurses assigned to surgery. In filling the genes of the first set of chromosomes, only the times available for each surgery are considered according to the availability of surgeons and the availability of the surgical room for each surgery. But for the second set of chromosomes, in addition to the availability of nurses and doctors in the allotted hours, attention should be paid to allocation to optimize (minimize or maximize) the objective functions of the problem. All four objectives of the problem directly depend on the way of allocation of anesthesiologists and nurses. For this reason, in the proposed hybrid algorithm, the focus is on the second set of chromosome genes. Therefore, the proposed algorithm is similar to the NSGA-II algorithm, and the only difference with NSGA-II is the presence of a loop of the VNS algorithm after crossover and mutation operators.

Fig. 7 shows the Pseudocode of the algorithm. The start of the proposed algorithm is with a set of random solutions, and every time the main loop of the algorithm is repeated, a certain fraction of the initial solutions (Pc) are selected to perform the intersection operation to reproduce. Two sets of chromosomes (two solutions) are selected for crossover operation, and according to Fig.3, the two-Point Crossover structure is used for reproduction. In most proposed hybrid algorithms of genetics and neighborhood search, the neighborhood structure of VNS is replaced by the mutation operator. But in our proposed model, both crossover and mutation operators are applied, and then the neighborhood structures defined for the VNS algorithm are used to specific genes of the chromosomes. The defined neighborhood structures for the model are presented in Fig.8.

Neighborhood Structure 1:
- Random selection of a row from the solution matrix (each row represents a group of surgical staff)
- Random selection of 2 genes in the selected chromosome string (*C1* and *C2*)
- Swap 2 selected genes with each other

Neighborhood Structure 2:
- Random selection of a row from the solution matrix (each row represents a group of surgical staff)
- Random selection of 2 genes in the selected chromosome string (*C1* and *C2*)
- Insert the second gen (*C2*) just before the first gen (*C1*)

Neighborhood Structure 3:
- Random selection of a row from the solution matrix (each row represents a group of surgical staff)
- Random selection of a block in the selected chromosome string
- Reversing the genes of the selected block

Neighborhood Structure 4:

- Random selection of a row from the solution matrix (each row represents a group of surgical staff)
- Random selection of two blocks in the selected chromosome string
- Swap 2 selected blocks with each other

Pseudocode of NSGAVNS

```
Input: nPop, Pc, Pm, Max.it, L_max, VNS_Max.it;
Define the set neghborhoods structures N_L (L=1,…, L_max)
Generate Initial Pop;
Population evaluation;
Performing non-dominated sorting and crowding distance;
For i=1 to Max.it do
For j=1 to round [(Pc × nPop)/2];
Select two individuals: (X1 , X2) randomly;
Apply two Point Crossover (X1 , X2)→(X′1 , X′2);
End for
For j=1 to round [(Pm × nPop)]
Select an individual: X randomly;
Apply mutation X→X′;
End for
For j=1 to VNS_Max.it
Select an individual: S  randomly;
L=1;
While (L<=L_max)
S′= Shaking (S, N_L);
S″= Local search (S');
if f(S″)≺f(S)
Replace S  with S″;
L=1;
        Else
             L=L+1;
        End while
     End for
Combine offspring and parents;
Assign rank based on Pareto dominance sorting algorithm and calculate the crowded distance of individual
based on rank and crowded distance to Select the best nPop individual;
End for
Output: best Pareto front;
```

Fig.7. Pseudocode of the proposed NSGAVNS hybrid algorithm

Experimentation and computational results

At the beginning of this section, the comparative indicators of problem solving algorithms are introduced. In the following, the case study is briefly presented. Then, the algorithm's parameters are tuned, and then the comparative analysis of algorithms is done. All algorithm implementations are coded using MATLAB R2016.b software and run on a personal computer with a 2.20 GHz Intel Core i5 Duo CPU and 8 GB memory.

Metrics used to compare algorithms

In this section, the improvement made by the model is evaluated based on real data, and the performance of MOPSO, NSGA-II, SPEA-II, and NSGAVNS algorithms is compared. To compare These algorithms, indicators of spacing metric (*SM*), mean ideal distance (*MID*), diversity metric (*DM*), and CPU time have been used.

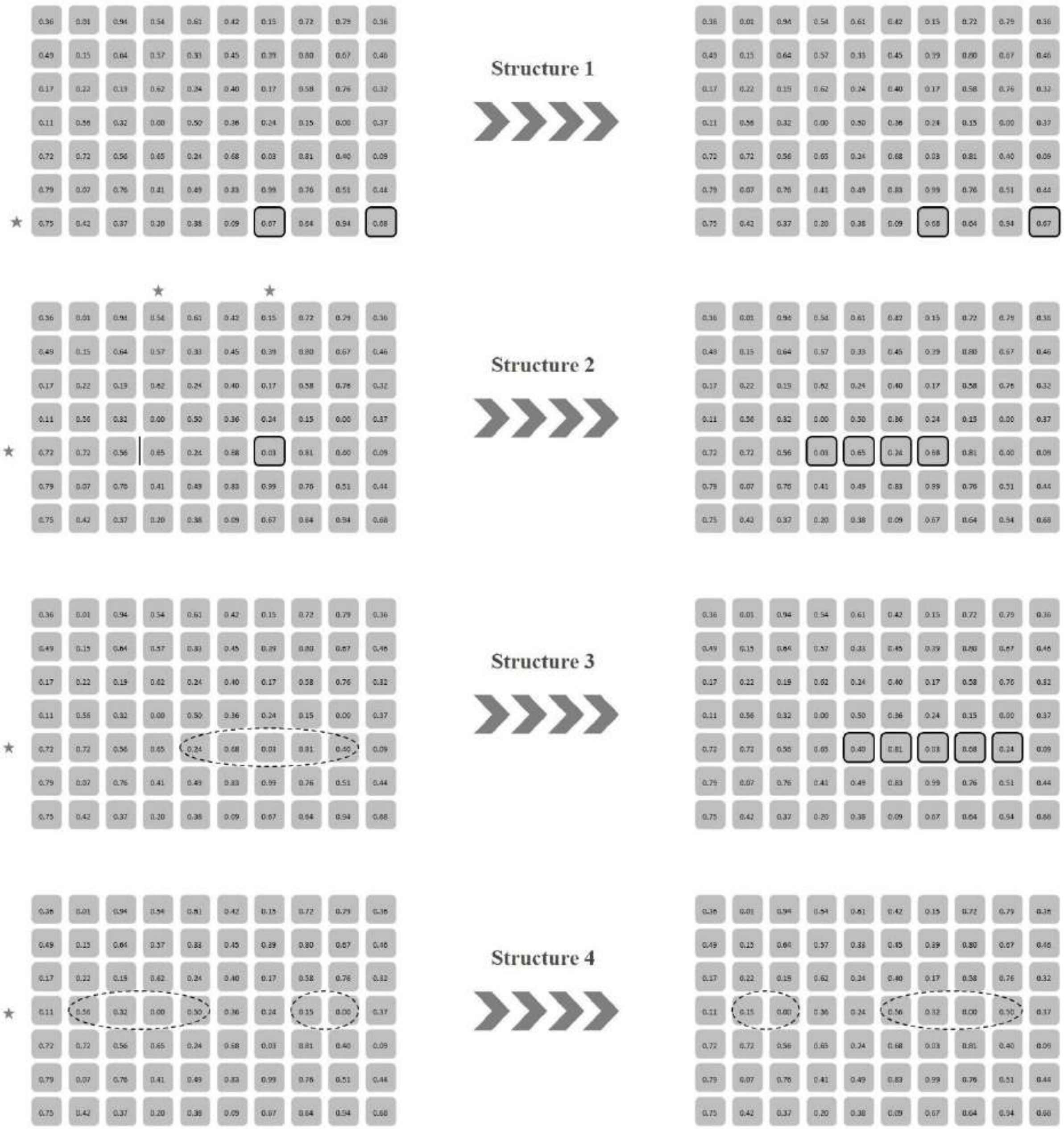


Fig.8. Neighborhood structures of NSGAVNS

To compare the values of criteria to each other, it is necessary to descale these values. For this purpose, the Relative Percent Difference (*RPD*) has been used. Obviously, the lower the RPD value, the better. This measure is calculated as equation (48):

$$RPD = \frac{S_i - S_{Best}}{S_i} \times 100 \tag{48}$$

where S_i represents the solution of algorithm i and S_{best} represents the best solution of algorithms.

Case study

The data are actual data from Razi Hospital in Qazvin province in Iran. These data are related to 1994 surgeries for 26 consecutive weeks (from September 2020 to March 2021) and include the number of surgeries, the duration of each surgery, and information about nurses, anesthesiologists, and surgeons. The hospital's strategy for scheduling surgeries is continuous. Based on the collected data from the duration of each surgery, we defined the time parameter as triangular fuzzy for each surgery. By considering time blocks of a certain length of time, we turn this into a discrete parameter.

Parameter setting and the obtained results

The values of the parameters of the solving algorithms impact their performance. The appropriate value for the parameters of metaheuristic algorithms prevents excessive repetition of the algorithm, which includes a wide range of different parameters, and the problem is solved in less time. To tune the parameters of the algorithms, there are various methods for the statistical design of experiments based on factorial designs. Although the use of full factorial designs provides full confidence regarding the performance of algorithm parameters, with the increase of factors and levels of each factor, the use of full factorial designs becomes very time-consuming and, in some cases impossible. Because in this situation, a huge number of experiments are needed to determine the best levels of the factors. For this purpose, fractional factorial designs are used to determine the optimal levels of factors. Utilizing the Taguchi approach, instead of performing all possible states of an experiment, only a fraction of all its states are tested to achieve the best combination of levels of different parameters. For example, for the MOPSO algorithm, there should be 5^6 trials, which is a high number. While using the factor design of L25 orthogonal arrays, only 25 trials can obtain the best combination of different parameter levels.

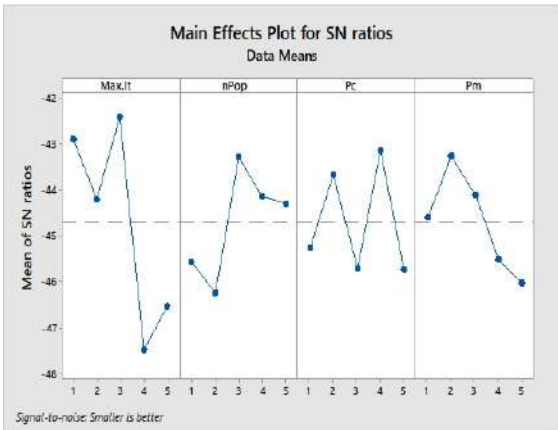
In the Taguchi method, the signal-to-noise ratio is used, and the optimal level of factors (problem parameters) is the level with more *S/N*. The value of *S/N* ratio is calculated using equation (49)

$$S / N_{ratio} = -10\log\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right) \tag{49}$$

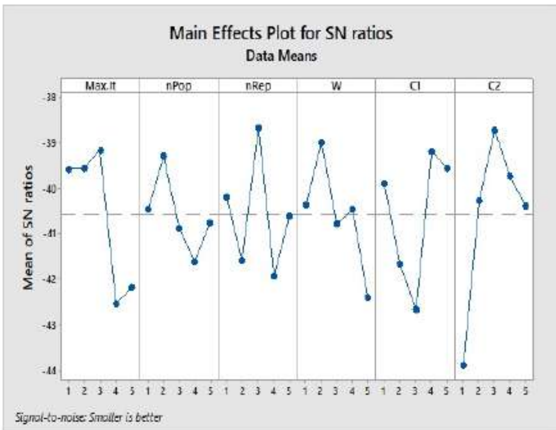
where S is the mean response variable, N represents the standard deviation, n is the number of trials for orthogonal arrays, and y_i is the *RPD* of the *ith* row of the orthogonal array.

In this paper, three metrics *SM*, *MID*, and *DM* are applied as performance measures for the Taguchi experiment results. After calculating each of the metrics and before calculating the *S/N* ratio, the data is scaled with the *RPD* equation.

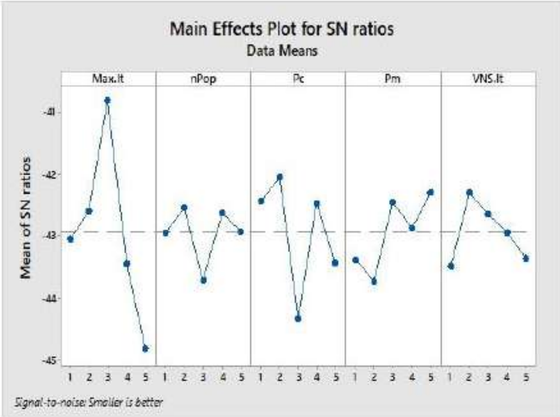
Using Minitab software, the results of Taguchi tests are determined to determine the best levels of problem parameters. The main effects of S/N ratio are shown in Fig. 9, and the levels of selected algorithm factors are shown in Table 3.



NSGA-II & SPEA-II



MOPSO



NSGAVNS

Fig. 9. Main effects plot for S/N ratio

Table 3: Calibrated parameter levels for tuning parameters and optimal values of parameters

Algorithms	Factors	Levels					Optimal Level
		1	2	3	4	5	
NSGA-II	Max.it	50	100	150	200	250	150
SPEA-II	nPop	100	125	150	200	250	150
	Pc	0.5	0.6	0.7	0.8	0.9	0.8
	Pm	0.2	0.3	0.4	0.5	0.6	0.3
MOPSO	Max.it	50	100	150	200	250	150
	nPop	75	100	125	150	200	100
	nRep	40	60	80	100	120	80
	w	0.25	0.3	0.35	0.4	0.45	0.3
	C1	1	1.15	1.3	1.45	1.6	1.45
	C2	1	1.15	1.3	1.45	1.6	1.3
NSGAVNS	Max.it	50	100	150	200	250	150
	nPop	75	100	125	150	200	100
	Pc	0.5	0.6	0.7	0.8	0.9	0.6
	Pm	0.2	0.3	0.4	0.5	0.6	0.6
	VNS_Max.it	0.1	0.2	0.3	0.4	0.5	0.2

Comparison of algorithms

As previously mentioned, *CPU time*, *MID*, *SM*, and *DM* metrics are used to evaluate the performance of problem solving algorithms. For this purpose, the data of 26 weeks (6 months) of the case study has been collected, and the average results of 10 runs have been considered the final result. The results of the evaluation of four criteria are shown in Tables 4 and 5. According to Table 4, the NSGAVNS algorithm performed best in all four metrics. In comparison the SPEA-II algorithm performed the worst in the three metrics. The SPEA-II algorithm has the second best performance among the four algorithms after NSGAVNS regarding solution uniformity in the solution space. The NSGA-II algorithm has performed poorly in all four metrics, and the MOPSO algorithm is second best algorithm in 3 out of 4 metrics, after the proposed hybrid algorithm. Algorithm efficiency analysis, Fig.10 shows the average and least significant difference (*LSD*) of all four algorithms in a box diagram. For the *SM*, *MID*, and *CPU time* metrics, a lower average, and for the *DM* metric, a high average indicates more Reliability. Also, for each metric, the smaller the data range, the stronger the algorithm's efficiency. Based on Fig.10 (a), which compares the algorithms based on the *MID* metric, the NSGAVNS algorithm is the best in terms of quality and efficiency, while the MOPSO algorithm is the worst in both conditions. According to Fig.10 (b) and considering the SM metric, the NSGAVNS algorithm is the best. Based on the DM metric shown in Fig.10 (c), the NSGAVNS algorithm has the highest reliability, but the efficiency of this algorithm is lower than the SPEA-II algorithm. Fig.10 (d) shows that the average run time of the NSGAVNS algorithm is significantly lower than other algorithms. In general conclusion, the NSGAVNS algorithm can be considered the best algorithm for solving the model presented in this paper.

Although Table 4 indicates the values of the comparison metrics of the algorithms, we use the Wilcoxon sign rank test to show statistically significant differences between the algorithms. The results of this test are shown in Table 7, based on which, in both *MID* and *DM* metrics, the NSGAVNS algorithm is significantly different from other algorithms. In the SM metrics, the NSGAVNS algorithm has a significant difference with the NSGA-II and MOPSO algorithms. Still, in comparison of the SM metric, there is no significant difference between the NSGAVNS and SPEA-II algorithms. Fig.11 shows the run time of the algorithms. Based on that, the run time of the NSGAVNS algorithm in all problems, without exception, is less than other algorithms. Therefore, in general, the NSGAVNS algorithm is an effective algorithm for solving the presented model.

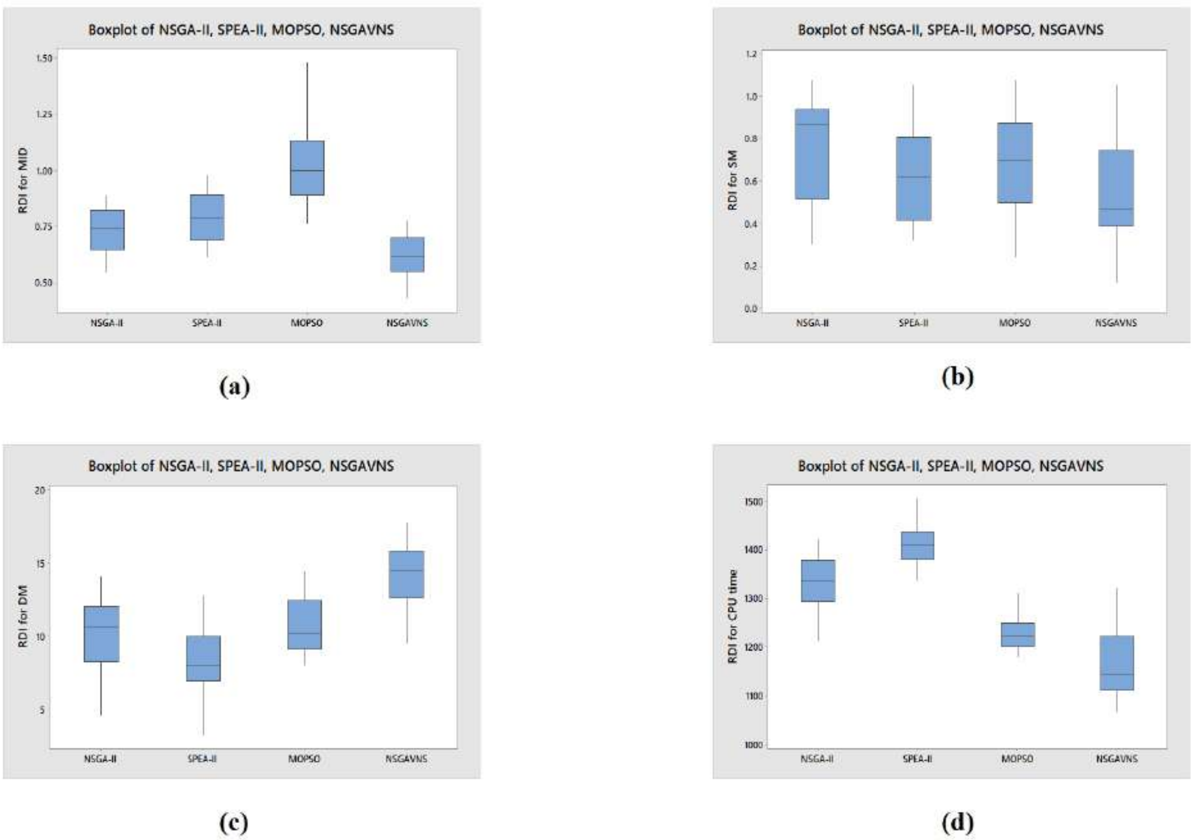


Fig. 10. Boxplots for comparison of algorithms based on evaluation metrics.

Table 7: Wilcoxon signed rank test for comparison indices of the proposed algorithm (significance level = 0.05).

Algorithms	MID	SM	DM
NSGAVNS vs. NSGA-II	0.00220727 (p-value < α)	0.00240294 (p-value < α)	0.00000208616 (p-value < α)
NSGAVNS vs. MOPSO	2.98023e-8 (p-value < α)	0.0200698 (p-value < α)	9.83477e-7 (p-value < α)
NSGAVNS vs. SPAE-II	0.0000221392 (p-value < α)	0.374003 (p-value > α)	2.98023e-8 (p-value < α)

Tables 5 and 6 show the average values of the Pareto front solutions of objective functions for each of the 26 problems for a set of 5 runs and actual objective function values, respectively. Based on the results obtained from the objective function values, the improvement in the solution for the presented model is quite evident. For justice in working hours, the standard deviation of the working hours of staff is considered. For the case study, the value of standard deviation was equal to 912 units. With the presented model, this value has decreased significantly. For all three metaheuristic algorithms, this number has decreased. So that in the solution with the MOPSO algorithm, which has the least improvement for this objective function, the value of the standard deviation has reached 696 units. It means that it has decreased by about 24 units. This number is 110 for the NSGAVNS Algorithm. That is, 88% reduction, which is a significant reduction and shows the good performance of the proposed heuristic algorithm. The proposed model has also performed well in reducing the overtime cost of the operating room. The overtime cost for the case study during the time horizon was equal to 527 monetary units. But with the presented model, this amount has decreased. The lowest reduction is related to MOPSO and SPEA-II algorithms, which is about 30% cost reduction. This value for the NSGAVNS algorithm is equal to 234 units. It means a reduction of about 54% in the cost of overtime, which is a significant reduction in the operating room costs. Also, the index defined to increase attention to the tendency of staff to work overtime was equal to 13.2 units, and this index is equal to 20.4, 18.9, and 36 for NSGA-II, SPEA-II, and MOPSO algorithms, respectively and for NSGAVNS algorithm it is equal to 56.3. Therefore, in all algorithms, this amount of improvement is significant and the most improvement is for the proposed heuristic algorithm. The total standard deviation of the idle times of the staff, which was used as an index to create the frequency, was equal to 10041 for the studied case. But in all algorithms, it has decreased by at least 53%. The biggest decrease is for the NSGAVNS algorithm, the value of this index has reached 1319 with an almost 87% decrease. Therefore, regardless of the problem solving algorithm, the presented model has fulfilled all the intended goals well. The best solution to minimize the overtime cost belongs to the NSGAVNS algorithm, and then the NSGA-II algorithm is the second best algorithm to achieve this goal. The NSGAVNS algorithm has a better solution than other algorithms for maximizing attention to the surgical staff's willingness to do overtime. Then the MOPSO algorithm has a favorable performance compared to other algorithms. The best improvement for creating a time break for surgical team members to rest between different surgeries belongs to the NSGAVNS algorithm. It has provided the best Pareto solutions for all four objective functions of the problem. In general, the NSGAVNS algorithm provided the best values among the four algorithms, and the improvement made in the planning of nurses according to the actual hospital data is noticeable and has provided the best Pareto solutions for all four objective functions of the problem.

Table 4: Comparison of algorithms according to the evaluation metrics and CPU times

Problem	NSGA-II				SPEA-II				MOPSO				NSGAVNS			
	MID	SM	DM	Time	MID	SM	DM	Time	MID	SM	DM	Time	MID	SM	DM	Time
1	0.82	1.05	11.57	1451.7	0.61	0.63	9.37	1591.2	1.03	**0.30**	8.68	1466.4	**0.55**	0.42	**15.87**	**1325.4**

2	0.83	0.45	10.63	1465.9	0.76	0.57	7.03	1530.1	1.48	0.50	8.24	1497.6	**0.43**	**0.40**	**12.53**	**1310.3**
3	**0.54**	0.85	10.61	1373.2	0.87	**0.33**	3.20	1463.1	0.84	0.46	8.23	1499.3	0.70	0.45	**13.20**	**1274.8**
4	0.67	0.51	13.55	1405.8	0.68	0.66	6.04	1452.4	0.84	0.24	10.20	1525.7	**0.55**	**0.12**	**14.29**	**1301.7**
5	**0.61**	0.83	9.65	1399.5	0.79	**0.44**	12.84	1438.9	0.98	0.85	14.24	1481.5	0.62	0.89	**15.72**	**1265.8**
6	0.66	**0.76**	11.9	1361.5	0.72	0.83	11.18	1395.4	1.22	0.86	13.44	1465.9	**0.57**	0.96	**15.77**	**1307.3**
7	0.74	**0.34**	8.70	1414.5	0.94	0.41	10.66	1487.1	0.99	0.97	10.38	1513.3	**0.55**	0.89	**12.68**	**1292.9**
8	0.81	0.88	11.46	1390.9	0.62	0.42	10.02	1462.1	1.07	0.53	9.13	1514.7	**0.53**	**0.31**	**15.55**	**1299.2**
9	**0.61**	0.88	8.05	1465.8	0.80	**0.40**	7.62	1495.1	0.76	0.80	8.01	1517.7	0.75	0.74	**17.86**	**1283.1**
10	0.75	0.89	**14.17**	1471.2	0.78	0.87	6.68	1543.1	0.91	0.75	11.13	1596.1	**0.56**	**0.29**	13.93	**1315.4**
11	0.75	0.94	9.19	1454.1	0.74	0.46	7.79	1548.0	0.89	0.87	9.62	1565.0	**0.55**	**0.40**	**15.84**	**1304.4**
12	0.79	0.89	10.26	1411.5	0.86	0.73	10.89	1442.1	0.99	1.08	8.17	1519.4	**0.62**	**0.62**	**12.84**	**1279.9**
13	**0.61**	0.73	12.64	1399.0	0.98	**0.32**	7.07	1525.2	1.12	0.83	9.03	1522.3	0.78	0.56	**14.46**	**1272.4**
14	0.73	0.49	10.78	1483.9	0.98	1.01	8.58	1563.3	0.90	0.88	**12.47**	1517.3	**0.52**	**0.34**	12.20	**1300.8**
15	**0.66**	0.78	11.85	1415.9	0.86	0.56	8.03	1528.1	1.03	0.98	9.31	1485.9	0.70	**0.39**	**14.70**	**1276.0**
16	0.85	0.91	13.12	1384.6	0.69	0.61	10.26	1435.6	1.08	0.62	12.98	1500.8	**0.61**	**0.44**	**16.15**	**1289.7**
17	0.68	1.01	6.574	1407.6	0.90	0.94	6.81	1493.6	0.97	**0.49**	9.86	1526.1	**0.66**	1.06	**13.70**	**1282.0**
18	0.79	0.90	6.279	1437.9	0.69	0.77	8.33	1504.6	1.16	0.93	13.06	1557.0	**0.50**	**0.39**	**17.43**	**1305.9**
19	0.80	1.08	6.875	1459.2	0.68	0.89	7.44	1529.9	1.27	**0.81**	**14.51**	1566.7	**0.65**	0.96	12.46	**1277.3**
20	**0.66**	0.94	**12.40**	1393.4	0.74	**0.38**	7.60	1403.2	0.89	0.47	9.24	1515.7	0.69	0.59	9.46	**1284.2**
21	0.61	1.06	5.65	1424.0	0.79	0.39	6.27	1469.7	0.83	0.64	12.51	1495.3	**0.57**	**0.34**	**14.49**	**1268.4**
22	**0.61**	0.52	8.34	1421.5	0.96	1.06	8.98	1475.6	1.01	0.59	9.89	1522.2	0.68	**0.47**	**10.41**	**1264.4**
23	0.83	**0.70**	13.20	1412.4	**0.65**	0.80	10.12	1432.7	1.02	1.01	12.38	1496.7	0.75	0.77	**16.54**	**1299.4**
24	0.84	**0.34**	10.70	1396.1	0.89	0.43	7.91	1404.2	0.89	0.52	12.24	1492.5	**0.71**	0.68	**15.90**	**1269.3**
25	0.83	1.02	11.55	1426.8	0.98	0.63	6.05	1497.2	1.28	0.50	10.50	1490.6	**0.55**	**0.46**	**12.31**	**1282.3**
26	0.89	0.77	4.60	1389.6	0.81	0.66	8.04	1448.4	1.24	0.55	11.57	1466.8	**0.74**	**0.47**	**16.01**	**1251.9**
Mean	0.73	0.79	10.17	1334.8	0.8	0.62	8.26	1407.6	1.03	0.69	10.73	1234.6	**0.62**	**0.55**	**14.32**	**١٢٤٠,٢**

Table 5: Objective Values obtained from solving sample problems.

	NSGA-II				SPEA-II				MOPSO				NSGAVNS			
Problem	Z1	Z2	Z3	Z4	Z1	Z2	Z3	Z4	Z1	Z2	Z3	Z4	Z1	Z2	Z3	Z4
1	191	285	2.6	3557	316	273	24.8	2097	426	342	22.5	2753	57	269	41.5	983
2	316	291	15.9	4970	283	355	5.4	1426	703	587	23.4	7333	127	253	38.2	1183
3	141	303	7.1	1830	113	299	3.8	1453	689	380	39.4	3780	114	262	68.2	936
4	129	304	31.7	4359	166	232	4.2	1886	670	395	46.2	4067	117	214	67.6	1091
5	248	299	20.2	3962	250	507	19.9	1802	929	304	45.8	6301	157	269	65.1	997
6	167	302	10.3	2763	147	463	21.4	2370	741	344	31.5	6258	129	242	40.7	1038
7	144	293	26	3510	143	429	26.3	2395	412	246	29.4	3243	90	211	76.1	1615
8	203	318	17.2	4843	168	253	24.4	2002	729	421	34.2	6220	138	223	46.9	1748
9	307	309	5.6	4560	204	250	16.6	2297	611	362	36.1	2575	79	219	45.2	1327
10	98	275	25.3	5179	299	277	19.9	2687	430	445	32.8	5057	81	200	80.5	1829
11	116	232	31.3	1608	271	447	21.8	1351	798	262	38	4336	108	208	45.7	1164
12	111	265	32.2	1719	237	393	33.1	1973	719	230	30.9	2478	132	212	39.5	1179
13	193	271	27.5	2026	200	451	32.4	2401	739	311	40.5	4675	96	212	59.5	1354
14	330	241	14.1	1817	163	329	12.3	2354	576	296	45	5652	95	229	83.5	1057
15	278	253	13.5	4062	186	404	33.4	2606	669	295	43.9	5776	122	228	67.6	1150
16	212	300	35.3	1928	253	514	33.8	1293	514	283	46.7	3965	164	261	58.3	1071
17	309	336	40.6	4886	203	419	10.5	1550	643	428	43.7	4728	81	226	53.4	1476
18	141	315	29.8	1818	167	216	17	2598	945	534	33.7	4206	105	216	70.2	1482
19	130	284	32.1	2611	251	419	14.9	2429	552	436	30.9	5822	76	231	49.2	1385
20	165	260	5.6	4113	187	376	28.9	2023	852	457	37.3	5214	105	234	61.1	1306
21	206	239	8.3	3827	307	485	12.1	2564	744	290	20.3	5922	100	207	44.9	1698
22	162	304	10.4	4004	195	411	18.4	1814	791	529	24	6399	86	212	42.6	1733
23	341	306	10.2	4314	288	356	10.9	1343	965	407	45.8	3413	113	272	50.9	1365
24	204	226	42.2	4584	148	298	16.2	2262	830	235	41.7	4792	148	206	71.2	1573
25	203	334	28.9	3084	293	320	22.4	٢501	815	509	38.3	2632	153	294	45.7	1321
26	304	292	5.4	3243	112	370	7.6	2012	613	309	34.5	2895	92	263	49.7	1226
Mean	206	286	20.4	3430	213	367	18.9	2057	696	370	36	4634	110	234	56.3	1319

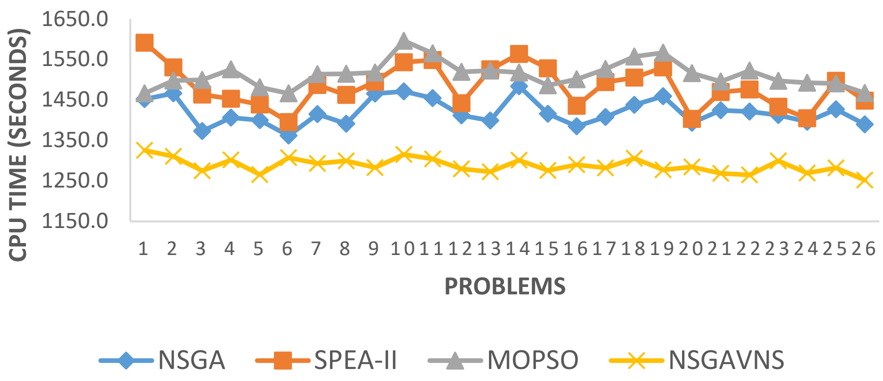


Fig. 11. Comparison of CPU time of algorithms in 26 problems.

Table 6: Actual Objective function values for 26 case study problems

	Case study			
Problem	**Z1**	**Z2**	**Z3**	**Z4**
1	800	647	8	10917
2	819	706	21.7	8325
3	1080	398	5	10535
4	938	436	21.1	11695
5	1066	522	7.2	9782
6	866	616	9.9	10553
7	993	377	14.7	8911
8	829	557	13.5	10018
9	813	470	6.1	11742
10	1063	382	17	11852
11	757	470	19.1	9621
12	876	653	13.8	8258
13	1069	565	3.3	11493
14	984	506	15.1	9166
15	874	511	16.2	11909
16	1086	564	4.5	9264
17	991	372	16.7	10760
18	794	702	7.3	8690
19	734	495	18.3	9239
20	1042	418	11.2	9525
21	1089	368	15.8	11016
22	857	748	12.7	9577
23	760	584	14.8	11713
24	767	539	14.9	8676
25	962	670	21	8560
26	814	424	14	9262
Mean	912	527	13.2	10041

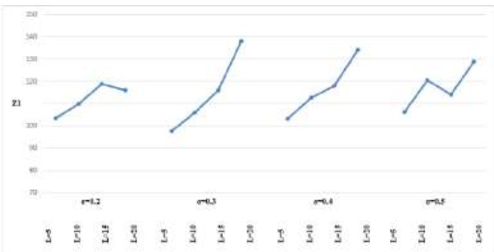
Sensitivity Analysis

Table 8 shows the normalized values of the objective functions based on changes in fuzzy confidence level and the length of the time block. Fig.12 shows the variability of the objective function values according to the two mentioned parameters. According to the results, there is no specific pattern between the change of the parameters α and L and the value of the $Z1$ function. But α and L for $Z2$ have a direct effect. For healthcare department managers, the ideal situation is to minimize staff members working hours. Because in this case, the overtime time (and the possibility of needing overtime) will be reduced. Therefore, reducing the value of the

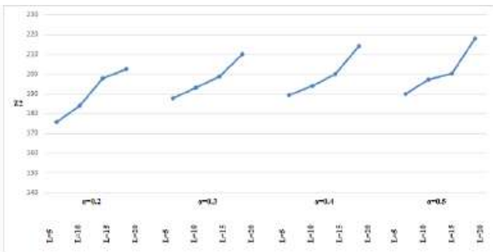
L parameter and the *α* parameter to some extent will bring the managers closer to this goal. *Z3* value has no direct or inverse relation with the *L* value, but it has a direct relation with the α value. Because with increasing *α*, the duration of surgery increases. Therefore, the possibility of the need for overtime increases, and due to the willingness of most staff members to do overtime, attention to their demands increases. The value of the objective function *Z4* has no apparent relationship with the changes in the parameter *α*. However, the *L* parameter has a direct relationship with the objective function value. Therefore, as *L* becomes smaller, the sum of the standard deviations defined in the *Z4* function decreases, which is favorable for the presentation model. Also, the value of two parameters, *α* and *L*, has a direct and inverse relationship with the program execution time, respectively.

Table 8: Objective function values based on the change in Fuzzy confidence level and the length of the time slot.

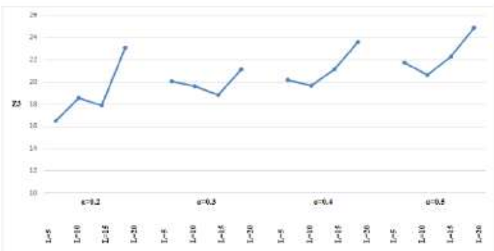
Objective function	L	α=0.2	α=0.3	α=0.4	α=0.5
Z1	5	103.6	110.1	119	116.1
Z2		175.9	184.2	198	202.7
Z3		16.47	18.55	17.86	23.07
Z4		3742	3823	3837	3906
Z1	10	97.72	106	116.2	138.1
Z2		187.7	193.1	198.7	210.1
Z3		20.07	19.64	18.83	21.11
Z4		3640	3714	3752	3812
Z1	15	103.2	112.7	118	134.2
Z2		189.5	194.2	200.1	214.2
Z3		20.2	19.7	21.1	23.6
Z4		3756	3801	3829	3992
Z1	20	106.4	120.5	114.3	129.1
Z2		189.9	197.1	200.5	218
Z3		21.73	20.62	22.31	24.89
Z4		3763	3822	3879	3943



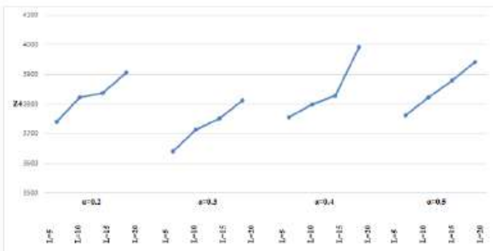
Z_1



Z_2



Z_3



Z_4

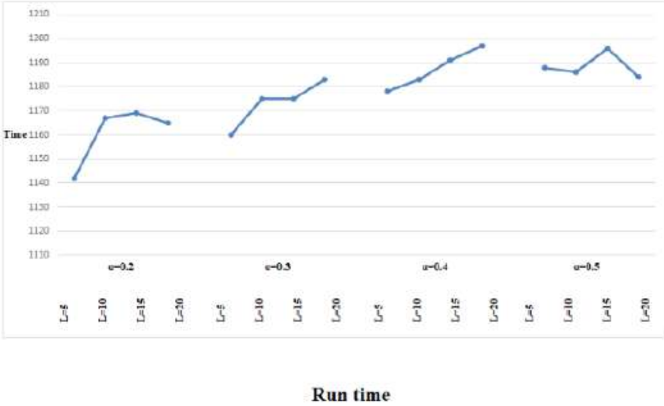


Fig. 12. Behavior of objective functions and run time for sensitivity analysis of α and L parameters

Conclusions and managerial insights

In this paper, a novel multi-objective model was proposed, which, in addition to paying attention to staff willingness to do overtime and reducing the total overtime cost, also considered fairness in the amount of useful work time of staff members and the frequency of idle time of each staff member during the shift to create break times. Minimizing the idle time for hospital resources, both human and non-human resources, has always been one of the concerns of managers and decision makers of healthcare systems. However, reducing it to zero is unattainable in most cases. Considering this issue, in this paper, the idle time of each nurse and anesthesiologist is equally divided between the different surgeries they participated in. Also, to establish fairness in the amount of working time of the surgical team staff, the allocation of this personnel to the surgical teams was done so that the total standard deviations of the idle time of staff members from its average are minimized. Due to the complexity of the nonlinear mathematical model and since this problem is NP-hard, solving the problem required the use of metaheuristic algorithms. For this, three algorithms, NSGA-II, SPEA-II, and MOPSO, were used to solve the problem and a new structure was introduced to display the chromosomes to improve the performance of the algorithms. In addition to these three algorithms, the NSGAVNS algorithm, an improved NSGA-II hybrid algorithm based on variable neighborhood search (VNS), was introduced. Due to the uncertainty of surgery time, we considered the time of each surgery as fuzzy. To evaluate the performance of the proposed model, 6-month data from the Elective Surgery Department of Razi Qazvin Hospital were tested.

Comparing the results of the presented model with the actual values planned by the hospital showed that the presented model will significantly improve the planning. In addition to paying attention to fairness in the workload and reducing overtime costs of the hospital, it creates rest times for nurses and anesthesiologists. Creating an interruption, however short, prevents the continuous and uninterrupted presence of staff members in two consecutive surgeries. To evaluate the performance of four algorithms, the metrics of comparison of Pareto solutions, run time, and value of objective functions were used. Based on all three indices, the NSGAVNS hybrid algorithm presented the best performance among the 4 algorithms.

Determining rest times for surgical department staff in the presented model provides new managerial insight. The existence of idle time during the working hours of employees is unavoidable. In addition, many studies and research have been conducted on the positive impact of employees' rest time on improving performance and reducing human errors. In many of these studies, it has been pointed out that short but high-frequency rest periods per shift are better than one or two long rest periods. Despite the researchers pointing out these important issues, there is a lack of a mathematical model that takes these issues into account. In our model, the unavoidable idle times of the employees are considered as their rest time and between the surgeries assigned to each one, and the idle time is not increased. Furthermore, in most articles on surgical staff scheduling, the size of the surgical team is assumed to be fixed. For this reason, many of these researches are not general and cannot be used in all hospitals and surgical theaters. Therefore, we considered the size of the surgical team as non-fixed so that the model has more flexibility to be implemented in natural environments.

The most crucial management insights obtained from the results are as follows:

- Creating equality in the working hours of employees: The total standard deviations of the idle time of each employee during the planning horizon have decreased from 912 to 110.
- Reduction of overtime cost: Overtime cost has been reduced from 527 units to 234 currency units.
- Increased attention to employees' willingness to do overtime: The defined index has risen from 13.2 to 56.3.
- Creating rest time between two consecutive surgeries assigned to staff: Total deviation from the standard length of blocks of idle time between two successive surgeries for employees has decreased from 10041 units to 1319 units.
- Flexibility in the size of surgical teams: Contrary to the models presented in the operating room Staff scheduling articles, The size of the surgical team (number of nurses and anesthesiologists) is always considered constant. In our model, the size of the surgical team can be changed.

Future directions for this study could include the following:

- Rest times for each staff member of the surgery department should be based on the severity of the assigned surgeries.
- Minimizing all staff members' idle time and balancing the rest time of each staff member are considered simultaneously.
- In addition to elective surgeries, emergency surgeries can also be considered.
- Emergency and urgent surgeries can be considered Simultaneously.
- Uncertainty of the presence of staff members at work on some days can be considered Simultaneously.

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