# New nurse scheduling problem considering burnout factor and undesirable shifts under COVID-19 (A real case study) 

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#### Abstract

In recent years, the outbreak of COVID-19 has led to burnout of healthcare personnel. Accordingly, more attention should be paid to nurses scheduling and their preferences. The Nurse Scheduling Problem (NSP) as an optimization concept provides suitable nurses' schedules by focusing on the system requirements. In this study, a new NSP is developed in which the factors and consequences of nurses' burnout are considered simultaneously. In the proposed model, new constraints are formulated to define the undesirable shifts. Due to the seniority rules, it is tried to restrict the numeral of these shifts in the generated timetable to improve the burnout of nurses. In addition, an attempt is made to fairly allocate the requested leave of nurses by considering their leave days during the previous horizons. In the presented model, the timetable of nurses is flexible to cope with the absence of employees, and the required personnel are covered by changing shifts among nurses. To solve the developed problem, Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) are coded, and their results are compared with GAMS in different test problems. Taguchi method has been applied for parameter tuning of these algorithms. The final results prove that the GA outperforms PSO both in obtained solution and CPU time. GA has only a $0.22 \%$ optimality gap on average. Finally, the proposed model is implemented in an actual case study in Iran. The generated timetable improves nurses' performance and the level of medical services by controlling the causes and consequences of burnout.


Keywords: COVID-19, burnout, nurse scheduling problem, particle swarm Optimization, Genetic Algorithm

## 1- Introduction

In hospitals, manpower management is important due to the continuous provision of care and treatment services. In this regard, nurse scheduling is necessary to provide quality services and meet patients' needs. In arranging nurses' timetables, work shifts are allocated to them according to hospital regulations and other assumptions. The NSP, which is a subset of scheduling concepts, performs this function to provide a quality timetable (Ramli et al., 2019). The way shifts are arranged can affect nurses' lives and cause them psychological problems.

[^0]Accordingly, it is necessary to provide an appropriate schedule that takes into account the willingness of nurses and human factors (Amindoust et al., 2021). Consequently, wide studies on nursing scheduling problem have been conducted. In most studies, a mathematical model (based on a set of factors) is proposed for assigning shifts to nurses over a certain period. Labor laws and hospital requirements are considered the most important restrictions in this scheduling (Jafari et al., 2015). However, nurses also have some priorities for work shifts and days off (Legrain et al., 2018). The satisfaction of these assumptions and constraints simultaneously complicates this problem. Accordingly, the NSP is classified as an NP-hard concept (Nasiri and Rahvar, 2017). Therefore, various methods have been proposed to solve the NSP, among which metaheuristic and artificial intelligence approaches have acceptable efficiency.

Recently, due to the outbreak of COVID-19 and the increasing workload of healthcare personnel, nurse scheduling has been considered an increasingly important issue. In this critical situation, the schedule should be provided such a way that in addition to applying the classical requirements, the factors affecting the performance of nurses are also improved. This study is done with the incentive of providing an efficient optimization model for nurses scheduling by considering human factors. Burnout is one of the parameters that have been considered in the ergonomic problems, which means mental fatigue and reduced physical ability due to the high workload and long-term work (Azmoon et al., 2018). Burnout is a common crisis in the health area, particularly among nurses. There are various causes for employee burnout. Consecutive shifts, shortage of nursing staff, a feeling of unfairness in working conditions, high-risk work environment, inflexible schedules, and team conflict are among the agents affecting job burnout. This significant human factor has consequences, the most common of which are: nurses' illness, job errors, reduction in staff efficiency, unexpected absences, and leaving the job (Lima et al., 2023). Control of this factor for NSP can impact the productivity of human resources and the level of medical services. In this study, by confining the undesirable condition and fairly assigning requested leave days to nurses, job dissatisfaction and burnout are reduced. Considering ergonomic factors and improving the parameters affecting the efficiency of employees enhance the medical services and the satisfaction of society.

In this research, some new relations are developed to define undesirable shifts, and the allocation of such shifts is limited to reduce burnout. Considering the condition of COVID-19 and the increase in the possibility of staff being absent in the assigned shifts, a framework is considered in which shift change is performed easily and the schedule can be updated with the least changes. Furthermore, the status of nurses' leave on the previous horizons is considered, in order not to discriminate in the allocation of requested leave for nurses.
The final goal of this research is to formulate an efficient optimization model for nurse scheduling under crisis while improving the burnout of healthcare personnel by controlling undesirable conditions. The following are the main innovations of this work:

- Considering ergonomic factors and burnout in the nurse scheduling problem.
- Fair allocation of requested leave to nurses based on their leave days in previous horizons.

In this study, the concept of burnout caused by working conditions under Covid-19 is incorporated in the NSP. To do this, the reasons for nurses' burnout and its subsequences are considered simultaneously in developing the scheduling model. In this process, new constraints are formulated to control the main causes of burnout. In addition, an efficient approach to overcome the nurses' unexpected absence as a common consequence of burnout is developed. In this strategy, non-deterministic methods of fuzzy and robustness are not used to define the stochastic parameter. These techniques may complicate problem-solving and make the modeling process difficult. Instead, constraints adapted from the concept of shift change are defined and the absence of nurses is compensated by a trade of shifts between nurses. This helps to control uncertain events without defining any new parameters and losing optimal solutions. However, the development of the NSP based on the burnout factor is a research gap that has been addressed in this study. Another innovation of this work is the allocation of requested leave by nurses considering the timetable of previous horizons. In this process, leave requests are divided into two categories: normal requests and requests related to high-demand days. Accordingly, a constraint is considered for approval of normal leave requests. In addition, the objective function tries to approve the second type of leave for nurses who had less leave in previous periods. This helps
to increase the job satisfaction of nurses and reduce discrimination among employees. To solve the optimization problem, a GA has been applied and a department of Imam Khomeini Hospital in Arak, Iran, has been considered to provide a schedule for a month during the COVID-19 pandemic.

The rest of the paper is as follows: The most recent and prominent literature on the NSP is investigated in section 2. In section 3, the problem description and the mathematical programming model are proposed. The solution approaches and algorithms process are described in section 4 . Then in section 5, the random problems are solved and the real case study is presented with computational results. Finally, the most important results and suggestions for future studies are presented in section 6.

## 2- Literature review

The nurse scheduling problem is an attractive subject that has been addressed in many studies. Several researchers have provided an overview of the literature on the field of NSP (Abdalkareem et al., 2021). Different solving processes have been used to deal with the problem, the most popular of which are: exact approaches and heuristic techniques (Rahimian et al., 2017). In modeling this problem, different hypotheses and constraints have been considered.
There are different research in which apply exact methods to tackle the NSP. In this approach, mathematical programming methods have been used for solving the problem, such as Binary Goal Programming (Azaiez and Al Sharif, 2005), Constraint Programming (Soto et al., 2013), Integer Programming (Santos et al., 2014), Mixed-Integer Mathematical Modeling (M’Hallah and Alkhabbaz, 2013 and Benazzouz et al., 2017), TwoStep Multi-Objective Programming (Nasiri and Rahvar, 2017), Stochastic Programming (Bagheri et al., 2016) and Fuzzy Mathematical Modeling (Jafari et al., 2015). Using these methods, the optimal timetable for the NSP is provided. But in the face of problems with large dimensions, solving the problem takes a long time (Turhan and Bilgen, 2020).

Considering the complexity of the NSP, other efficient approaches have been devised. In recent years, numerous meta-heuristic and hybrid techniques have been suggested to deal with the NSP, such as particle behavior-based algorithms (Ramli et al., 2017), improved Harmony Search Algorithm (Cetin Yagmur and Sarucan, 2019), Quantum Annealing method (Ikeda et al., 2019), a hybrid Ant system and Search Algorithms (Ramli et al., 2019), heuristic processes derived from the concept of Column Generation (Strandmark et al., 2020), Modified GA (Saraswati et al., 2021), a hybrid of GA and Tabu Search (Adebayo et al., 2022), using the Nelder-Mead improver in an Artificial Bee Colony (Muniyan et al., 2022), the simultaneous combination of Integer Programming and PSO algorithm (Turhan and Bilgen, 2022), Whale Optimization Algorithm (Sadeghilalimi et al., 2023), and a hybrid approach of deep neural network-based mechanism and mixedinteger optimization (Chen et al., 2023).

In each study, considering different hypotheses and focusing on several new factors, a novel mathematical model for NSP has been presented. Yilmaz (2012) provided a new optimization procedure for labor shifts related to nurses. Focusing on the idle waiting time of nurses and rest after a work shift were the most important hypotheses considered in this study. Jafari and Salmasi (2015) by calculating the numeral of staff according to the needs of the hospital, proposed a proper model for NSP. In their approach, the presence of nurses in the final working days of the prior month was investigated and the objective function focused on work preferences and weekends of nurses. El Adoly et al. (2018) presented a method for nurses' scheduling based on the structure of a multi-commodity network flow. In this model, the objective was to minimize the total cost of regular shifts, overtime, and the cost of the head nurse. Hamid et al. (2020) presented an efficient model for nurses' scheduling by dividing staff based on skills and focusing on nurses' preferences and compatibility of staff decisions. The produced schedule increased staff satisfaction and reduced job errors. Turhan and Bilgen (2022) developed a new scheduling model in which the assignment of work shifts and days off to nurses was considered as well as how to unit allocation based on the skill and seniority of the employees. By combining the exact method and PSO, they provided near-optimal timetables for scheduling treatment staff. Zhuang and Yu (2021) proposed a new model for the outpatient NSP, focusing on the effect of the law change on personnel scheduling. In this study, hypotheses related to total working hours and rest time between periods were considered based on new labor laws. The results showed the effect of these changes on the workload and the numeral of workdays for nurses. Nobil et al. (2022) formulated an optimization model for scheduling a
homogeneous workforce to minimize whole-wage costs while determining sufficient staffing to meet demand. In this model, considering the difficulty of working night shifts and vacations, the wages of these shifts were different compared to others. The model implementation results indicated optimal use of staff and reduction of payroll costs. Due to the uncertainty in the parameters and the constant change of conditions, Hassani and Behnamian (2021) presented a scenario-based mathematical model for NSP. In this model, a pessimistic approach was applied to deal with the uncertainty. The use of this model, taking into account the uncertainty in determining the workload and parameters of the problem, increased staff satisfaction and improved services. Ceschia et al. (2023) suggested a model for scheduling healthcare staffing in Italian hospitals. In this approach, a complex model was presented in which comprehensive assumptions and constraints related to the NSP as well as the provisions of staff employment contracts were formulated. The simulated annealing algorithm was used to solve the novel model. The result was the production of optimal timetables approved by the hospitals' management.

Amindoust et al. (2021) developed a new optimization problem to provide an efficient schedule, considering the workload and increasing fatigue of nurses during the pandemic of COVID-19. In this approach, nurses' scheduling was done fairly and nurses had the least fatigue during the planning horizon. Klyve et al. (2022) presented an efficient method to control nurses' fatigue by combining personal sleep models and the NSP. The formulated model, focusing on determining the optimal number of human resources and developing fair timetables, led to a significant reduction in staff fatigue. The generated timetables helped to improve the health of nurses and reduce individual errors. Rerkjirattikal et al. (2020) considered a programming model for nurses' scheduling fairly with the aim of job satisfaction and retention of manpower. They practically determined the satisfaction factors using interview and questionnaire techniques. The resulting schedule simultaneously considered the balanced workload and preferences of the nurses. Khalili et al. (2020) formulated a multiobjective programming method for NSP, emphasizing the importance of staff's short breaks during work shifts and increasing their efficiency. In addition to the common rules and requirements in the NSP literature, they applied ergonomic factors for nurse scheduling. In this model, the skill level is considered an important parameter, and nurses are simultaneously assigned to shifts and skill levels. Reducing nurses 'fatigue during work shifts, minimizing the allocation of consecutive morning-evening shifts, and paying attention to nurses' reluctance to work in some shifts and days were the most important benefits of the produced schedules. In Table 1, the mentioned studies are listed in comparison with the present research.
Despite these studies, providing a nurse scheduling model that has the least burnout and job stress is a necessity to pursue. In this study, considering the nursing shortage and workload due to the COVID-19 pandemic, we propose a new approach for undesirable shifts and try to control burnout by limiting the allocation of these shifts to nurses. Other contributions of the paper for the NSP are: applying nurses' preferences based on seniority factor, considering the status of nurses' leave in the previous horizon for allocating the requested leave in the current horizon, and flexibility of the schedule against the absence of nurses. We implement the formulated problem in an actual case study and apply the GA to solve the problem.

Table 1. The list of the proposed literature in the NSP

| Row | Researcher | Year | Modeling and problem solving method |  |  |  | Human factor |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  | Singleobjective | Multiobjective | Exact method | Meta/ Hybrid | Fatigue | Stress | satisfaction | Burnout |
| 1 | $\underset{\text { Azaiez and } \mathrm{Al}}{\text { Sharif }}$ | 2005 | * |  | * |  |  |  | * |  |
| 2 | Yilmaz | 2012 | * |  | * |  |  |  |  |  |
| 3 | M'Hallah and Alkhabbaz | 2013 | * |  | * |  |  |  | * |  |
| 4 | Santos et al | 2014 | * |  | * |  |  |  |  |  |
| 5 | Jafari and Salmasi | 2015 | * |  |  | * |  |  | * |  |
| 6 | Jafari et al | 2015 | * |  | * |  |  |  | * |  |
| 7 | Bagheri et al | 2016 | * |  | * |  |  |  | * |  |
| 8 | Benazzouz et al | 2017 | * |  | * |  |  |  |  |  |
| 9 | Nasiri and Rahvar | 2017 |  | * | * |  |  |  | * |  |
| 10 | Ramli et al | 2017 | * |  |  | * |  |  | * |  |
| 11 | El Adoly et al | 2018 | * |  | * |  |  |  | * |  |
| 12 | Ikeda et al | 2019 |  |  |  | * |  |  |  |  |
| 13 | Ramli et al | 2019 | * |  |  | * |  |  | * |  |
| 14 | Rerkjirattikal et al | 2020 |  | * | * |  |  | * | * |  |
| 15 | Khalili et al | 2020 |  | * | * | * | * |  | * |  |
| 16 | Strandmark et al | 2020 |  |  |  | * |  |  |  |  |
| 17 | Hamid et al | 2020 |  | * |  | * |  | * | * |  |
| 18 | Zhuang and Yu | 2021 | * |  | * |  |  |  |  |  |
| 19 | Hassani and Behnamian | 2021 | * |  |  | * |  |  | * |  |

Table 1. Continued

| Row | Researcher | Year | Modeling and problem solving method |  |  |  | Human factor |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  | Singleobjective | Multiobjective | Exact method | Meta/ <br> Hybrid | Fatigue | Stress | satisfaction | Burnout |
| 20 | Amindoust et al | 2021 |  | * |  | * | * |  |  |  |
| 21 | Turhan and Bilgen | 2022 | * |  |  | * |  |  |  |  |
| 22 | Nobil et al | 2022 | * |  | * |  |  |  | * |  |
| 23 | Adebayo et al | 2022 |  | * |  | * |  |  |  |  |
| 24 | Muniyan et al | 2022 |  |  |  | * |  |  |  |  |
| 25 | Klyve et al | 2022 | * |  |  | * | * |  |  |  |
| 26 | Sadeghilalimi et al | 2023 |  |  |  | * |  |  | * |  |
| 27 | Chen et al | 2023 |  |  |  | * |  |  |  |  |
| 28 | Ceschia et al | 2023 |  | * |  | * |  |  |  |  |
| 29 | Current research | 2023 | * |  | * | * |  |  | * | * |

## 3- Problem description

In hospitals and health centers, the provision of optimal services and patient satisfaction depends on the performance of nurses (Kieft et al., 2014). Therefore, identifying and controlling the factors that affect job performance is essential. One of the most important of these factors is burnout due to the shortage of personnel and increasing workload (Lee et al., 2003). In addition, critical conditions such as the pandemic of COVID-19 can exacerbate this problem (Guray Guler and Geçici, 2020). Accordingly, it is necessary to generate an appropriate timetable that takes into account the parameters affecting burnout and simultaneously satisfies the hospital demand and nurses' priorities. To do this, we formulate an optimization problem for scheduling nurses in an Iranian public hospital operating in three consecutive shifts: morning (M), evening (E), and night (N). According to interviews with the matron and nurses, job stress, discrimination in the approval of leave requests, ignoring staff wishes, and assigning undesirable shifts due to the staff shortage are effective parameters in burnout among nursing staff. Assigning two shifts per day to nurses (morning-evening, morning-night, and evening-night) and allocating a night-morning shift pattern indicate the undesirable condition of type 1 and type 2 , respectively. In the proposed model for controlling burnout and workload balance, the allocation of these patterns to staff is limited. In addition, the number of nurses' leave days in previous periods is considered in order to fairly assign leave requests to the nurses on the current planning horizon. Due to the COVID-19 pandemic in recent years and the increase in the number of staff absences, we propose a new constraint that contributes to the flexibility of the schedule so that demand can meet with minimal changes to the timetable. Nurses are grouped according to seniority rules, and this classification is considered to formulate the scheduling model. According to seniority rules, nurses with more experience are superior to less experienced ones. In this research, the experience factor is measured by years of working in the organization. These regulations are determined by the matron and ward head nurses based on their background in human resource
management. In this study, the rules of seniority are considered for applying the nurses' preferences in the final schedule, assigning undesirable conditions to personnel, and also the process of shift change among nurses. Hence, the objective function of the proposed model is to minimize deviances from nurses' preferences based on their seniority and the total deviation of their leave requests. Other assumptions of the proposed scheduling model based on the case study are as follows:

- The hospital's estimate of the staff needed for different shifts must be supplied accurately.
- The working hours for each shift are as follows: 7:15 A.M to 2:30 P.M (first shift), 1:30 P.M to 8:00 P.M (second shift), and 7:00 P.M to 8:00 A.M (third shift).
- Productivity law can affect the length of work shifts. Based on this rule, the working hours of staff in night shifts and weekends of the planning period are computed 1.5 times. This is a measure to motivate nurses to work unpleasant shifts.
- The monthly workload of a nurse must range between at least and at most specified working hours for his/her. If a leave day is assigned to a nurse, leave time (according to the labor law is equivalent to 6.5 hours) will be subtracted from his/her working hours.
- In the provided timetables, should not be defined more than two following shifts for each nurse.
- In the scheduling process, the allocation of nurses to the night-night shift pattern is not possible.
- Each nurse should work a specified amount of weekend shifts during the planning period. This helps to fairly allocate weekend shifts to the nurses.
- The shift change among personnel is done based on the head nurse's approval. Therefore, a nurse can trade his/ her shift with other nurses in the same category due to unforeseen events.
- Assigning undesirable and consecutive shifts to particular nurses (including those who are pregnant, breastfeeding, or have underlying diseases) is not allowed.
- The head nurse is off on weekends and does not work in the evening and night shifts on weekdays, and only should be present in the morning shifts during the weekdays of the planning horizon. These assumptions are ignored if the head nurse has other preferences.


## 3-1- Mathematical programming model

To develop the optimization problem, the main elements of the model are determined. Then, the objective function and the different constraints of the problem are presented.

Table 2. The main elements of the proposed optimization model

## Sets and indices:

| I | Set of staff/nurses $\{1, \ldots, p n\}$ |
| :---: | :---: |
| $i, i$ | Index of nurses ( $\left.i, i^{\prime} \in I\right)$ |
| $o$ | Index of head nurse ( $o \in I$ ) |
| $I_{m}$ | Set of particular nurses ( $I_{m} \subseteq I$ ) |
| $I_{r}$ | Set of nurses applying for leave (on the high request days) who had the least leave on the previous horizons ( $I_{r} \subseteq I$ ) |
| $T$ | Set of days $\{1, \ldots, t n\}$ |
| $t, t^{\prime}$ | Index of days. ( $t, t^{\prime} \in T$ ) |
| $T_{1}$ | Set of holidays and weekend ( $T_{1} \subseteq T$ ) |
| $T_{2}$ | Set of weekdays ( $T_{2} \subseteq T$ ) |
| $T_{3}$ | Set of days with high leave requests ( $T_{3} \subseteq T$ ) |
| $J$ | Set of work shifts $\{M, E, N\}$ |
| $j, j$ | Index of shifts ( $j, j^{\prime} \in J$ ) |
| K | Set of seniority of nurses $\{1, \ldots, n s\}$ |
| $k$ | Index of seniority ( $k \in K$ ) |
| $I_{k}$ | Set of nurses of seniority K ( $\left.I_{k} \subseteq I\right)$ |
| Parameters: |  |
| $w h_{i}$ | Working hours for nurse i |
| oh | Maximum total overtime for a nurse |
| $l e_{j}$ | Length of shift j in hours |
| $b r$ | Length of leave time in hours |
| $t n$ | Number of days (current horizon) |
| $f r_{\text {it }}$ | 1, if a nurse has asked to leave for a certain day; 0 Otherwise |
| $D_{j t}$ | Hospital's estimate of the nurses needed for a certain shift-day |
| $U_{\text {max }}$ | Maximum weekend shifts that can be defined for staff |
| $U_{\text {min }}$ | Minimum weekend shifts that can be defined for staff |
| $N_{k}$ | Maximum of undesirable shifts that can be defined to staff of group k |
| $\gamma_{k}$ | The weight of nurses' preferences of group k |
| $g_{i}$ | 1, if a nurse has attended the last night shift of the prior planning period; 0 otherwise |
| $g s_{i}$ | 1, if a nurse has attended the shift evening-night shift pattern on the last day of the prior planning period; 0 otherwise |
| $\mu_{i j t}$ | 1, if a nurse preference to work a certain shift-day; 0 otherwise |
| $\varphi_{i t}$ | 1, if a nurse preference to be off on a certain day; 0 otherwise |
| $v_{j t}$ | 1.5, if a certain shift-day be subject to the productivity rule; 1 otherwise |
| $\omega_{1}, \omega_{2}, \omega_{3}$ | The weighting factor of the objective function terms |
| M | A large number |
| Decision Variables: |  |
| $\mathrm{x}_{\mathrm{ijt}}$ | It is 1 if nurse i works in a certain shift-day; 0 otherwise |
| $y_{\text {it }}$ | It is 1 if nurse i be off on a certain day; 0 otherwise |
| $\chi_{i t}^{1}$ | It is 1 if nurse i works two shifts on a certain day; 0 otherwise |
| $\chi_{i t}^{2}$ | It is 1 if nurse i is allocated to night-morning shift pattern; 0 otherwise |
| $\rho_{i i t t}$ | Linearization variables |

## - Objective function and constraints.

$\operatorname{Min} \omega_{1} \sum_{k \in K} \gamma_{k}\left(\sum_{i \in I_{k}} \sum_{j \in J} \sum_{t \in T} \mu_{i j t}\left(1-x_{i j t}\right)\right)+\omega_{2} \sum_{k \in K} \gamma_{k}\left(\sum_{i \in I_{k}} \sum_{t \in T} \varphi_{i t}\left(1-y_{i t}\right)\right)$

$$
\begin{equation*}
+\omega_{3} \sum_{i \in I_{r}} \sum_{t \in T_{3}} f r_{i t}\left(1-y_{i t}\right) \tag{1}
\end{equation*}
$$

Subject to:

$$
\begin{align*}
& \sum_{i \in I} x_{i j t}=D_{j t} \quad \forall t \in T, j \in J  \tag{2}\\
& w h_{i} \leq \sum_{j \in J} \sum_{t \in T} v_{j t} l e_{j} x_{i j t}+\sum_{t \in T} b r f r_{i t} y_{i t} \leq w h_{i}+o h \quad \forall i \in I  \tag{3}\\
& 1-y_{i t} \leq \sum_{j \in J} x_{i j t} \leq 2\left(1-y_{i t}\right) \quad \forall i \in I, t \in T \tag{4}
\end{align*}
$$

$x_{i j t}+x_{i(j+1)(t-1)}+x_{i(j+2)(t-1)} \leq 2 \quad \forall i \in I ; t \in T: t \neq 1, j=1$
$x_{i j t}+x_{i(j+1) t}+x_{i(j+2)(t-1)} \leq 2 \quad \forall i \in I ; t \in T: t \neq 1, j=1$
$g s_{i}+x_{i j t} \leq 1 \quad \forall i \in I ; t=1, j=1$
$g_{i}+x_{i j t}+x_{i(j+1) t} \leq 2 \quad \forall i \in I ; t=1, j=1$
$U_{\min } \leq \sum_{j \in J} \sum_{t \in T_{1}} x_{i j t} \leq U_{\max } \quad \forall i \in I: i \neq 0$

$$
\begin{align*}
& x_{i j t} \leq \sum_{\substack{i^{\prime} \in I_{k} \\
i^{\prime} \neq i}}\left(y_{i^{\prime} t}-\rho_{i^{\prime} j^{\prime} t t^{\prime}}\right) \quad \forall k \in K, i \in I_{k}, t, t^{\prime} \in T: t \neq 1, t^{\prime}=t-1, j \in J, j^{\prime}=3  \tag{8c}\\
& x_{i j t^{\prime}}+y_{i t} \leq \rho_{i j t t^{\prime}}+1 \quad \forall k \in K, i \in I_{k}, t, t^{\prime} \in T, t \neq 1, t^{\prime}=t-1, j=3  \tag{8d}\\
& x_{i j t^{\prime}}+y_{i t} \geq 2 \rho_{i j t t^{\prime}} \quad \forall k \in K, i \in I_{k}, t, t^{\prime} \in T, t \neq 1, t^{\prime}=t-1, j=3  \tag{8e}\\
& 1-M\left(2-x_{i j t}-x_{i j^{\prime} t}\right) \leq \chi_{i t}^{1} \leq 1+M\left(2-x_{i j t}-x_{i j^{\prime} t}\right)  \tag{9a}\\
& \forall i \in I: i \neq o ; t \in T ; j, j^{\prime} \in J: j<j^{\prime} \\
& 1-M\left(2-x_{i j t-1}-x_{i j^{\prime} t}\right) \leq \chi_{i t}^{2} \leq 1+M\left(2-x_{i j t-1}-x_{i j^{\prime} t}\right)  \tag{9b}\\
& \forall i \in I: i \neq o, t \in T: t \neq 1 ; j=3, j^{\prime}=1 \\
& 1-M\left(2-g_{i}-x_{i j t}\right) \leq \chi_{i t}^{2} \leq 1+M\left(2-g_{i}-x_{i j t}\right)  \tag{9c}\\
& \forall i \in I: i \neq o ; t=1 ; j=1 \\
& \sum_{t \in T} \lambda_{i t}^{1}+\lambda_{i t}^{2} \leq N_{k} \quad \forall k \in K, i \in I_{k}: i \neq o  \tag{10}\\
& \sum_{i \in I_{m}} \sum_{t \in T} \chi_{i t}^{1}+\chi_{i t}^{2}=0  \tag{11}\\
& x_{o j t}=1 \quad \forall t \in T_{2}, j \in J, j=1  \tag{12a}\\
& x_{o j t}=\mu_{o j t} \quad \forall t \in T, \quad j \in J  \tag{12b}\\
& y_{i t} \geq f r_{i t} \quad \forall i \in I, t \in T-T_{3}  \tag{13}\\
& x_{i j t} \in\{0,1\} \quad \forall i \in I, j \in J, t \in T  \tag{14a}\\
& y_{i t}, \chi_{i t}^{1}, \chi_{i t}^{2} \in\{0,1\} \quad \forall i \in I, t \in T  \tag{14b}\\
& \rho_{i j t t^{\prime}} \geq 0 \quad \forall i \in I, j \in J, t, t^{\prime} \in T \tag{14c}
\end{align*}
$$

Equation (1) indicates the objective function of the optimization model. This function is formed of 3 parts: minimizing the deviations of nurses' preferences for working shifts (the first part) and days off considering the effect of seniority factor (the second part), and minimizing the total deviation of leave requests related to the high requests days for nurses who had the least leave on the previous horizon (the third part). Constraint (2) ensures that the hospital's estimate of the nurses needed for a certain shift-day will be met. Constraint (3) Controls the shift allocation to nurses based on the allowed working hours and overtime during the planning horizon. In this constraint, the sum of the leave times and total hours shifts allocated to each nurse considering
productivity factor during the planning period is computed. The calculated number is the time that a nurse spends at paid labor, and it's between the predetermined time intervals. Constraint (4) indicates that each nurse can be allocated to at most two shifts per day and no shift is assigned to him/her on the days off. Constraint sets (5a)-(5d) forbid assigning more than two following shifts to staff, considering the condition working of the nurses on the last day of the prior planning period. Constraint (6) indicates that each nurse should work at least Umin and at most Umax of the weekend shifts during the scheduling period. It should be noted that this constraint is not raised for the head nurse due to the determined rules of case study. Assigning two consecutive night shifts to any nurse is not allowed. Constraints (7a) and (7b) guarantee this restriction, considering the last nurses' night shifts of the prior planning period. Due to the COVID-19 pandemic in recent years, the number of staff absences and requests for shift change between nurses has increased. This issue has caused frequent changes in the schedule and hassle for the head nurse. Constraints (8a) and (8b) guarantee that for each seniority class, there is at least one nurse on standby (with the identical class) who can be used as a replacement force in case of possible staff absence. These constraints make the schedule flexible against nurses' absence so that replacement nurses can be determined with less bother. It is assumed that these absences are short-term and may arise for one or two days. Note that constraint (8b) causes the mathematical model to be nonlinear. So, this constraint substitutes with equations (8c)-(8e) to deal with this problem. Constraints (9a) $(9 \mathrm{c})$ are an efficient approach to specify the undesirable shifts. Accordingly, assigning more than one shift per day to a nurse indicates undesirable conditions of type 1 (9a). Furthermore, working nurses in the nightmorning shift pattern indicates undesirable conditions of type 2 (9b), (9c). To control burnout, the allocation of these shifts to nurses should be limited. Constraint (10) does this by considering the seniority factor. Note that there is no obligation to allocate undesirable conditions to the head nurse, and these cases can only be raised for other nurses based on the rules of the under-study center. Constraint (11) ensures that no undesirable conditions are defined for particular nurses during the planning period. Constraint (12a) shows that the head nurse works morning shifts during the weekdays of the planning period. If the head nurse has his/her preferences, this equation is omitted and constraint (12b) applies. Constraint (13) ensures the leave request is applied to the nurses on ordinary days (days when leave requests are low in number). Finally, equations (14a)(14c) describe the type of decision variables.

## 4- Solution approach

## 4-1- Genetic algorithm

The GA is a particular version of evolutionary approaches first introduced by Holland (1975). The GA is inspired by the mechanism of nature to improve creatures and uses the survival of the fittest principle for optimization. This algorithm has acceptable efficiency for solving complex problems and can be exploited for a vast range of scheduling models (Amindoust et al., 2021). In the GAs, the proper definition of the chromosome plays a vital role in providing desirable and quality solutions (Habibnejad et al., 2019). In this study, as shown in figure 1, the assignment of work shifts to staff during the planning period is considered a chromosome or main variable of the problem. The proposed chromosome is a three-dimensional matrix where rows illustrate the nurses, columns represent shifts, and layers are used to show the days of the month. Each cell of this matrix is represented by 0 and 1 . A value of one indicates that the corresponding shift-day is assigned to the related nurse, and a value of zero shows that the corresponding nurse is not allocated to the related shift-day. Another key factor is the fitness function that is applied to assess the solutions and allocate values to chromosomes (Katoch et al., 2021). Equation 1 in section 3 is considered for calculating the fitness function's value. The main steps in the generation of the nurse schedule based on the applied GA are:

1. Random production of the initial timetables (initial population) and calculating fitness values.
2. Selection of tables (parents) and applying uniform crossover operator to generate new timetables (population of children). In this crossover, the children's data is randomly selected from the parents' data.
In this process, a binary chromosome is generated based on a uniform distribution. For the values of one, the first child receives the corresponding elements from the first parent, and the second child gets its features from the second parent. This operation for the zero value of the generated chromosome is done oppositely.
3. Select population members and use mutation operation aimed at creating evolutionary schedules (population of mutants). This operator makes new timetables by randomly changing the values of the prior tables. In this procedure, one of the elements of the considered parent is selected randomly. If the corresponding value is equal to one, it is replaced by zero. Also, if the selected value equals zero, it will be substituted with the one. In this way, the mutant children have a new characteristic that may not already be present among the previous population.
4. Merging initial and generated solutions, sorting these solutions according to the problem objective, and removing inappropriate solutions (generating a new main population).
5. Returning to the second step until the stop conditions (maximum numeral of iterations of the algorithm) are met.


Fig 1. The chromosome representation
In all these levels, the selection operation of tables (parents and individuals) is stochastic. The methodology of this algorithm is designed in figure 2, which is adapted from the standard GA for the nurse scheduling problem.


Fig 2. The GA process for generating nurses' schedules

## 4-2- Particle swarm optimization

Another efficient algorithm in the field of evolutionary computing is PSO. This algorithm proposes a suitable approach to optimize scientific problems by considering the collective behavior of social species of nature and the effect of swarming intelligence on achieving success (Gad, 2022). The PSO algorithm is often used to solve optimization problems due to its simple implementation structure and the provision of quality solutions (Wang et al., 2018). In this method, particles are equivalent to the main variables of the problem, and position, objective value, and velocity are considered the main characteristics of each particle. In this study, the particles are the same as the nurses' timetable along the planning horizon and equation 1 in section 3 is considered for calculating the particles' values. The following main stages are defined for implementing the PSO algorithm:

1. Determine the initial position of the particles randomly (generation population of particles).
2. Calculate the objective function value for each particle.
3. Initial comparison of particles and determination of the best particle by considering the particles' position and the value of the objective function.
4. Update the position and velocity of all particles according to the following equations:

$$
\begin{align*}
& V_{i}^{k+1}=W \cdot V_{i}^{k}+c_{1} r_{1}\left(P_{l b_{i}}^{k}-X_{i}^{k}\right)+c_{2} r_{2}\left(P_{g b}^{k}-X_{i}^{k}\right)  \tag{15}\\
& X_{i}^{k}=\left\{\begin{array}{lll}
1 & \text { if } & \operatorname{sig}\left(V_{i}^{k}\right)>r \\
0 & \text { otherwise }
\end{array}\right. \tag{16}
\end{align*}
$$

Where $V_{i}$ is velocity of the member $\mathrm{i}, X_{i}$ is location of the member i, $P_{l b_{i}}$ is optimal location of the member i (personal best), $P_{g b}$ is best location of the all population (global best), $r, r_{1}, r_{2}$ are stochastic number between 0 and $1, k$ is index of the iteration, W is inertia weight, $c_{1}$ is personal learning constant, and $c_{2}$ is social learning constant.
5. Evaluate particles' updated positions and new values of objective functions.
6. Compare the current position of each particle with its previous optimal location as well as the best collective location of the other particles (update the best particle).
7. Go to step 4 until the stop conditions (maximum numeral of iterations of the algorithm) are satisfied.

The above steps and the methodology of the considered PSO are illustrated in figure 3:


Fig 3. The standard PSO algorithm

Various approaches have been presented to improve the performance of the classic PSO and the feasibility of the problem. Some of the most common of these methods are: the optimal calculation of the learning coefficients, adding a penalty function to the minimizing objective, determining the velocity limits for particles, applying limits on particles' position, and using the velocity mirror effect. In this study, the penalty functions and the position limit method are simultaneously used to prevent infeasible solutions as well as improve the results. The following relation is applied for position limit method. This relation prevents particles from moving out of the initial space defined for them.
$X_{i B}=\min \left\{\max \left(X_{i}, X_{\min }\right), X_{\max }\right\}$

Where $X_{i B}$ is limited location of member $\mathrm{i}, \mathrm{X}_{\mathrm{i}}$ is location of the member $\mathrm{i}, X_{\text {min }}$ is defined lower bound, and $X_{\max }$ is defined upper bound.

After running the algorithm, penalty functions will be defined for the constraints that will not satisfied. Then, the average of the penalties will be minimized in the objective function. To do so, the cumulative approach is used to minimize violations in objective function. In this regard, relations (18) and (19) are considered:
$v_{i}=\frac{\left|\frac{g}{g_{0}}-1\right|+\left(\frac{g}{g_{0}}-1\right)}{2}$
$Z_{n}=Z+P(v)$
Where $P(v)$ is the average deviation, $Z$ is the initial objective function, $Z_{n}$ is the final objective function, $v_{i}$ is the violation of constraint $\mathrm{i}, g_{0}$ is the value of the right side in a constraint, and $g$ is the equation of left side in a constraint. Note that, it is assumed that all constraints are of the type less than or equal $\left(g<=g_{0}\right)$. In the following, the performance of the GA in comparison with the PSO and the exact method to solve the proposed model is evaluated for different random data. In addition, the proposed NSP for real data will be solved by the GA. The meta-heuristic algorithms are coded in MATLAB R2014a as well as the GAMS software is used to calculate optimal results. It should be noted that all calculations are performed using a personal computer (PC) with a 3.30 GHz Intel Core i3-3220 and 1.68 GB of RAM.

## 5- Computational results

## 5-1- Parameter Tuning

The parameter values of meta-heuristic algorithms are effective in providing quality solutions. The parameter setting of the proposed algorithms is done by the classic Taguchi method, which is one of the common techniques for the design of experiments. In this process, different tests are defined considering the main parameters of the solution algorithms and the numeral of levels selected for them. Table 3 shows the parameters of the proposed algorithms with their corresponding levels. According to the number of levels and parameters of each algorithm, the number of experiments designed for parameters setting of GA and PSO is equal to 27 . Finally, the tests determined are implemented for each algorithm then their results are analyzed to determine the appropriate combination of factors based on the signal-to-noise $(\mathrm{S} / \mathrm{N})$ ratio. The value of $\mathrm{S} / \mathrm{N}$ is computed by Minitab 14 so that its greater values at any level are more appropriate.

Table 3. Parameters of meta-heuristic algorithms at different levels

| Algorithm | Parameters | Level | Level | Level |
| :--- | :---: | :---: | :---: | :---: |
|  | Number of population (Npop) | 1 | 2 | 3 |
| GA | Maximum number of iterations (Max it) | 80 | 150 | 200 |
|  | Percentage of crossover (Pc) | 120 | 200 |  |
|  | Percentage of mutation (Pm) | 0.5 | 0.7 | 0.9 |
|  | Number of particles (Npcl) | 0.2 | 0.4 | 0.6 |
| PSO | Maximum number of iterations (Max it) | 100 | 150 | 200 |
|  | Personal learning constant (c1) | 80 | 120 | 200 |
|  | Social learning constant (c2) | 1.5 | 2 | 2.5 |
|  | Inertia weight (W) | 1.5 | 2 | 2.5 |
|  |  | 0.8 | 0.9 | 1 |

Figure 4 shows the means of the $\mathrm{S} / \mathrm{N}$ ratio for the determined parameters of the proposed algorithms.


Fig 4. Graph of $\mathrm{S} / \mathrm{N}$ ratios in GA and PSO

Due to these results and the selection of the higher output of the factors at each level, the proper values of the parameters are presented in table 4.

Table 4. Adjusted values for the parameters of the proposed algorithms

| Algorithm | Parameters Of Algorithms |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Npop/Npcl | Maxit | Pc | Pm | c1 | c2 | W |
| GA | 100 | 120 | 0.7 | 0.2 | - | - | - |
|  |  |  |  |  |  |  |  |
| PSO | 100 | 120 | - | - | 2 | 2 | 1 |

## 5-2- Random data

In this section, twenty numerical examples in different sizes have been randomly generated using uniform distribution to assess the scheduling model and solution approaches. Table 5 demonstrates the generated samples along with the results of solving the proposed model by meta-heuristic algorithms and the exact method. The GA and PSO algorithms are executed 10 times separately for each sample and the average objective function values of these instances and the corresponding implementation time are considered. Furthermore, the deviations of the solutions obtained by each algorithm compared to the exact method are calculated. As shown in this table, GA has a better performance compared to the other two methods for solving this model. The GA provides quality solutions with an average gap of $0.22 \%$ compared to the exact answers so that in most examples these solutions are equal to the exact solving. On a small scale, all three approaches can solve problems in a reasonable amount of time nevertheless on a large scale the exact method are not able to solve some examples. Problem-solving time by GA is acceptable for medium and large samples, but this time is longer in PSO and increases dramatically in the exact method. To better describe the performance of GA in solving the proposed model, consider the 14 th row of table 5 . According to the exact method, the objective function value is equal to 2.7 and the average of the solutions proposed by GA and PSO are 2.73 and 2.9. In addition, the solving time of the problem base on GA, PSO, and the exact method is 373 , 440, and 3070
seconds respectively. As shown in this example, the GA provides a suitable solution in a short time that has the least difference from the exact answer. In summary, quality solutions, solving large-scale problems, and reasonable solving time are the advantages of the GA.

Table 5. Comparison of GAMS, GA and PSO results

| Row | Dimensions $(\mathbf{i} * \mathbf{j} * \mathrm{t})$ | Exact Method |  | GA |  |  | PSO |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | Objective Value | Time (Seconds) | Average Solutions | Time (Seconds) | \% Deviation | Average Solutions | Time (Seconds) | \% Deviation |
| 1 | 8*3*10 | 10.6 | 28 | 10.6 | 28 | 0.00\% | 10.6 | 30 | 0.00\% |
| 2 | 9*3*11 | 7 | 52 | 7 | 30 | 0.00\% | 7 | 35 | 0.00\% |
| 3 | 10*3*12 | 7.2 | 32 | 7.2 | 34 | 0.00\% | 7.2 | 38 | 0.00\% |
| 4 | $11 * 3 * 12$ | 5.9 | 143 | 5.9 | 35 | 0.00\% | 5.9 | 39 | 0.00\% |
| 5 | $12 * 3 * 13$ | 3.6 | 142 | 3.6 | 38 | 0.00\% | 3.6 | 43 | 0.00\% |
| 6 | $13 * 3 * 7$ | 1.9 | 161 | 1.9 | 36 | 0.00\% | 1.9 | 39 | 0.00\% |
| 7 | $14 * 3 * 14$ | 2.7 | 235 | 2.7 | 190 | 0.00\% | 2.7 | 219 | 0.00\% |
| 8 | 16*3*15 | 1 | 205 | 1 | 209 | 0.00\% | 1 | 235 | 0.00\% |
| 9 | 17*3*18 | 2 | 397 | 2 | 224 | 0.00\% | 2 | 280 | 0.00\% |
| 10 | 18*3*19 | 1.7 | 3495 | 1.7 | 231 | 0.00\% | 1.7 | 270 | 0.00\% |
| 11 | $19 * 3 * 20$ | 1.9 | 2886 | 1.9 | 250 | 0.00\% | 1.9 | 295 | 0.00\% |
| 12 | 19*3*21 | 1.3 | 2360 | 1.3 | 256 | 0.00\% | 1.3 | 301 | 0.00\% |
| 13 | 20*3*22 | 2.1 | 18000 | 2.13 | 276 | 1.43\% | 2.2 | 332 | 4.76 |
| 14 | 22*3*23 | 2.7 | 3070 | 2.73 | 373 | 1.11\% | 2.9 | 440 | 7.41\% |
| 15 | $24 * 3 * 25$ | Na | 18000 | 3.7 | 400 | - | 3.9 | 481 | - |
| 16 | $25 * 3 * 26$ | Na | 18000 | 3.9 | 420 | - | 3.9 | 500 | - |
| 17 | $26 * 3 * 28$ | 4 | 15932 | 4.03 | 450 | 0.75\% | 4.4 | 545 | 10\% |
| 18 | $28 * 3 * 31$ | Na | 18000 | 5 | 483 | - | 5 | 568 | - |
| 19 | $30 * 3 * 40$ | Na | 18000 | 9.5 | 571 | - | 9.8 | 695 | - |
| 20 | $35 * 3 * 30$ | Na | 18000 | 5.1 | 533 | - | 5.3 | 637 | - |

Figure 5 illustrates the GA performance compared to the other two methods focusing on the problem-solving ability in various dimensions and providing quality solutions. As shown in this figure, the quality of the solutions generated by GA is equal to the exact answers. Accordingly, these evaluations prove the efficiency of GA to solve the proposed scheduling model.


Fig 5. Comparison of the objective values calculated by GA, PSO and the exact method

## 5-3- Case study

Imam Khomeini Hospital of Arak (Iran) is one of the health centers that have provided significant treatment measures during severe conditions of COVID-19 for responding to the needs of the community and patients. Increased hospitalization, infection of nurses with this virus, and staff shortages are some of the problems that occur in these critical situations. Therefore, we implement the proposed model in one of the departments of this hospital to evaluate the efficiency of this model in real life. This department has 21 midwives ( $\mathrm{i}=1, \ldots, 21$ ), all of whom are called nurses in this study. The head nurse ( $\mathrm{i}=1$ ) arranges the monthly timetable for the following period in a manual mode. Consecutive and undesirable shifts are not assigned to particular nurses ( $\mathrm{i}=20,21$ ) to maintain their physical and mental health. Scheduling is done in such a way that the hospital's estimate of the nurses needed for each shift $(\mathrm{j}=\mathrm{M}, \mathrm{E}, \mathrm{N})$ per day $(\mathrm{t}=1, \ldots, 30)$ is accurately met. Due to the fact that our study period is related to February 2021, the number of staff needed for defined shifts on holidays and weekends ( $\mathrm{t}=2,3,9,10,16,17,22,23,24,30$ ) are 5,4 , and 4 , respectively. This numeral is equal to 8,4 , and 4 for other days (non-holiday and weekdays). Note that holidays and weekends are determined according to the official Iranian calendar. All nurses are classified into 4 categories ( $k=1, \ldots, 4$ ) based on their work experience and seniority. The first category nurses have the highest seniority, and the fourth category nurses have the lowest seniority. Each of the nurses has preferences and requests for the following period, which are registered in the nurses' request book. These priorities will be incorporated into the final timetable as much as possible by the head nurse. In addition, she considers the working situation of employees in the last shifts of the prior planning period to prevent violations of the rules and requirements in the early days of the following horizon. Other information on the main parameters of the studied department is recorded in table 6. Furthermore, the characteristics of the nurses, their preferences, and leave days requests are detailed in table 7.

Table 6. Additional information for the parameters of the case study

| Assigned shift N to nurses <br> (last day of pre-horizon) | Assigned shift E-N to nurses <br> (last day of pre-horizon) | Maximum number of <br> undesirable shifts for category k. |
| :---: | :---: | :---: |
| $g_{7}=1 ; g_{11}=1 ; g_{14}=1 ; g_{18}=1$ | $g s_{19}=1$ | $N_{1}=1 ; N_{2}=1 ; N_{3}=2 ; N_{4}=2$ |
| $\mathbf{O h}=\mathbf{1 7 5}$ | $I_{r}=\{5, \mathbf{7 , 1 0 , 1 7 \}}$ | $U_{\min }=\mathbf{5}$ |$U_{\max }=\mathbf{7}$.

Table 7. Personnel information and the recorded requests of nurses in the studied department

| Index Of Nurses (i) | Seniority (k) | Work <br> Hours <br> (WHi) | Leave Days Request | Preferences For Days Off | Preferences For Working Shift |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  |  |  | Morning | Evening | Night |
| 1 | 1 | 130 | - | $\begin{gathered} \hline \hline 3,10,17,21,22,23,2 \\ 4,25,26 \end{gathered}$ | $\begin{gathered} \hline \hline 1,2,4,5,6,7,8,9,11,12,13, \\ 14,15,16 \\ 18,19,20,27,28,29,30 \end{gathered}$ | - | - |
| 2 | 1 | 130 | 6th | - | - | - | 7,14,28 |
| 3 | 1 | 130 | 1th | 3,4,5,6,7,8,9, 10 | 11,18 | - | 11,18 |
| 4 | 1 | 130 | - | 21,22,23 | - | - | 3,10,17,24 |
| 5 | 1 | 130 | 5th ; 6th | - | - | - | - |
| 6 | 1 | 140 | 4th | - | 3,10,17,24 | $\begin{aligned} & 1,5,6,7,8,11,12,13 \\ & 14,15,18,19,20,21 \\ & 22,25,26,27,28,29 \end{aligned}$ | - |
| 7 | 2 | 140 | 6th | - | - | - | - |
| 8 | 2 | 140 | 25th | 15,21 | 2,9,16,23,30 | - | 6,13,20,27,29 |
| 9 | 2 | 140 | - | 11 | - | $\begin{gathered} 1,2,5,7,8,12,14,15 \\ 16,19,20,21,22,23 \\ 25,26,27,28,30 \end{gathered}$ | 4,9,13,18,29 |
| 10 | 2 | 140 | 6th | 11,12 | - | $\begin{gathered} 1,3,4,5,7,8,9,14,15 \\ 16,17,19,20 \\ 22,23,24,26,27,29,30 \end{gathered}$ | $\begin{gathered} 2,10,13,18,21 \\ 25,28 \end{gathered}$ |
| 11 | 2 | 140 | ${ }^{-}$ | - | 4,13,20,25 | $\begin{gathered} 2,5,7,9,12,14 \\ 16,17,19,21,23,26 \\ 28,30 \end{gathered}$ | $\begin{gathered} 6,8,11,15,18,22 \\ 27,29 \end{gathered}$ |
| 12 | 3 | 150 | 16th | 2,3 | - | $\begin{gathered} 1,4,6,8,12,13,14,19 \\ 20,21,26,27,28,29 \end{gathered}$ | - |
| 13 | 3 | 150 | 6th | 4,11,18,25 | - | - | - |
| 14 | 3 | 150 | - | - | - | $\begin{gathered} 3,7,9,10,12 \\ 14,16,17,19,21,23 \\ 24,26,28,30 \end{gathered}$ | 3,10,17,24 |
| 15 | 3 | 150 | - | 27,28,29,30 | 1,5,13,19,26 | - | $\begin{gathered} \text { 1,3,5,10,13,17 } \\ 19,22,24,26 \end{gathered}$ |
| 16 | 3 | 150 | - | 1,2,3,4,5,6 | - | - | 7 |
| 17 | 4 | 160 | 6th | 10,17,22 | 9,16 | 9,16 | 2,14,21 |
| 18 | 4 | 170 | 30th | 4,24 | 3,23,25 | 3,23 | 2,10,17 |
| 19 | 4 | 170 | - | 25 | - | - | - |
| 20 | 4 | 160 | 6th | 15,16,17 | - | - | - |
| 21 | 4 | 160 | - | 24 | - | 1,6,11,12,14,20,28, 30 | 3,18,26 |

As shown in table 7, Nurse 8 has a leave request for day 25 of the planning horizon $\left(\mathrm{fr}_{8,25}=1\right)$. Also, Nurse 18 prefers to be off on Days 4 and 24 of the next planning horizon ( $\varphi_{18,4}=1, \varphi_{18,24}=1$ ) and working in the evening shift on Days 3 and $23\left(\mu_{18, \mathrm{E}, 3}=1, \mu_{18, \mathrm{E}, 23}=1\right)$. The head nurse agrees with the nurses' leave requests, except for days when these requests are high (like Day 6), in which case the nurses who had the least leave in previous periods are given priority. Note that the influences of seniority classes are considered in assigning these priorities to them. Here, these weights are calculated using the eigenvector method and equal $\gamma_{1}=0.4, \gamma_{2}=0.3, \gamma_{3}=0.2$, and $\gamma_{4}=0.1$ for each category.
Table 8：Generated time table for case study

|  | － | $\Sigma$ | $\bigcirc$ | $z$ | $z$ | O | O | $z$ | $\Sigma$ | ш | O | ш | $\Sigma$ | O | ш | － | $z$ | $\bigcirc$ | エ | $\Sigma$ | $\Sigma$ | ш | 5 | 4 | 4 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 굴 | $\Sigma$ | ш | $\Sigma$ | $\bigcirc$ | $\Sigma$ | ш | $\bigcirc$ | $z$ | $z$ | ш | $z$ | ш | $\Sigma$ | $z$ | $\bigcirc$ | $\bigcirc$ | $\Sigma$ | $\Sigma$ | $\Sigma$ | $\bigcirc$ | $\Sigma$ | 8 | 4 | 4 |
|  | $\stackrel{\infty}{\sim}$ | $\Sigma$ | 2 | $\Sigma$ | $\bigcirc$ | $\Sigma$ | ш | － | O | ш | $z$ | ш | $z$ | $\Sigma$ | ш | $\bigcirc$ | $\Sigma$ | $\Sigma$ | $\Sigma$ | $\bigcirc$ | $\Sigma$ | 0 | 8 | 4 | 4 |
|  | ㅊ | $\Sigma$ | $\bigcirc$ | $\Sigma$ | $\Sigma$ | $\Sigma$ | ш | O | z | ш | ш | z | ш | O | z | $\bigcirc$ | $\Sigma$ | $\bigcirc$ | $\Sigma$ | $\underset{\Sigma}{\lambda}$ | $\Sigma$ | 0 | 8 | 4 | 4 |
|  | $\cdots$ | $\bigcirc$ | $\Sigma$ | $\Sigma$ | $\Sigma$ | 0 | ш | $\Sigma$ | 0 | $z$ | ш | ш | $z$ | O | ш | $\underset{\Sigma}{\Sigma}$ | $\Sigma$ | $\Sigma$ | $\Sigma$ | O | 0 | z | 8 | 4 | 4 |
|  | へ 気 | 0 | $\Sigma$ | $\Sigma$ | ш | 2 | ш | $\Sigma$ | 工 | ш | $z$ | $\Sigma$ | $\Sigma$ | $\bigcirc$ | $z$ | ш | $\Sigma$ | $\bigcirc$ | $\Sigma$ | O | $z$ | $\Sigma$ | 8 | 4 | 4 |
|  | $\stackrel{7}{4}$ | $\bigcirc$ | $\Sigma$ | ш | $z$ | $\Sigma$ | $\Sigma$ | $\bigcirc$ | $\Sigma$ | $z$ | ш | O | 0 | ш | 0 | z | $\Sigma$ | $z$ | 0 | O | ш | 0 | 5 | 4 | 4 |
|  | $\stackrel{\sim}{\square}$ | $\bigcirc$ | O | 0 | $\bigcirc$ | $\Sigma$ | $\Sigma$ | $z$ | $\Sigma$ | ш | $\bigcirc$ | ш | $\Sigma$ | $z$ | ш | O | $\bigcirc$ | $\bigcirc$ | $\Sigma$ | $z$ | $z$ | ш | 5 | 4 | 4 |
|  | ㅊ 8 | $\bigcirc$ | $\Sigma$ | $z$ | $\bigcirc$ | $\Sigma$ | ш | $\Sigma$ | $\bigcirc$ | ш | ш | $z$ | $\Sigma$ | $\bigcirc$ | 0 | $z$ | ш | O | $\bigcirc$ | $\Sigma$ | $\bigcirc$ | 2 | 5 | 4 | 4 |
|  | 入i ${ }_{\text {ה }}$ | $\bigcirc$ | $\Sigma$ | $\Sigma$ | $\bigcirc$ | $\Sigma$ | ш | O | O | ш | $z$ | ш | $\Sigma$ | $\underset{\Sigma}{\Sigma}$ | ш | $\bigcirc$ | $\Sigma$ | $z$ | 2 | $\Sigma$ | $\Sigma$ | 0 | 8 | 4 | 4 |
|  | 응 | $\Sigma$ | $\Sigma$ | $\bigcirc$ | $z$ | $\Sigma$ | ш | $\bigcirc$ | $z$ | ш | ш | $\underset{\Sigma}{\Sigma}$ | ш | $\Sigma$ | $z$ | $\bigcirc$ | $\Sigma$ | 0 | $\bigcirc$ | $\Sigma$ | $\bigcirc$ | $\Sigma$ | 8 | 4 | 4 |
|  | $\cdots$ | $\Sigma$ | $\Sigma$ | $\bigcirc$ | $\Sigma$ | $z$ | ш | $\Sigma$ | $\bigcirc$ | ш | ш | ш | $z$ | $\Sigma$ | $\Sigma$ | $\Sigma$ | $\bigcirc$ | $z$ | $z$ | $\bigcirc$ | $\Sigma$ | 0 | 8 | 4 | 4 |
|  | $\cdots$ | $\Sigma$ | $\Sigma$ | $\Sigma$ | ш | $\bigcirc$ | ш | $\bigcirc$ | $\Sigma$ | $z$ | 2 | $z$ | $\Sigma$ | $\bigcirc$ | $\bigcirc$ | ш | $\Sigma$ | $\bigcirc$ | ш | $\Sigma$ | $\Sigma$ | $z$ | 8 | 4 | 4 |
|  | त | $\bigcirc$ | $\bigcirc$ | $\bigcirc$ | $z$ | $\Sigma$ | $\Sigma$ | $\Sigma$ | $\bigcirc$ | $\bigcirc$ | ш | ш | $\Sigma$ | ш | $z$ | $z$ | $\bigcirc$ | $\bigcirc$ | $z$ | $\Sigma$ | $\bigcirc$ | ш | 5 | 4 | 4 |
| $\underset{\sim}{n}$ | $\cdots$ | $\Sigma$ | 2 | $z$ | $\Sigma$ | $\bigcirc$ | $\bigcirc$ | $\bigcirc$ | $\Sigma$ | ш | $\bigcirc$ | ш | エ | 2 | ш | $\bigcirc$ | $\Sigma$ | $\stackrel{\text { 崖 }}{ }$ | $\bigcirc$ | $\bigcirc$ | $\bigcirc$ | $z$ | 5 | 4 | 4 |
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|  | －${ }^{+}$ | $\Sigma$ | $z$ | $z$ | $\bigcirc$ | $\Sigma$ | ш | － | O | ш | ш | ш | $\Sigma$ | $\Sigma$ | $\Sigma$ | 0 | $z$ | $z$ | $\Sigma$ | $\Sigma$ | $\bigcirc$ | $\Sigma$ | 8 | 4 | 4 |
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Due to the parameter values for the case study and solving the defined optimization problem by the GA, the nurses' schedule during February is generated according to table 8. As shown in this table, the hospital's estimate of the staff needed for different shifts is accurately met. Furthermore, the leave requested by nurses is fairly allocated to them. Except for the 6th, all nurses' leave requests are assigned to them. On the Day 6, the leave request of the nurses who had the least leave in previous periods is approved. In this schedule, undesirable shifts have been assigned to the nurses due to a staff shortage. But as is clear, the number of these shifts is very low.
Figure 6 depicts the numeral of assigned undesirable conditions to the nurses during the planning period. In this figure, the red line clearly shows the maximum number of these shifts in the nurses' schedule. Note that the maximum of undesirable conditions for nurses of categories 1 and 2 during the period is 1 , and the particular nurses are not assigned to these shifts. This helps reduce burnout and job stress for nurses.


Fig 6. Status of undesirable shifts in the schedule
Assigning weekend shifts to nurses is another matter parameter that has been considered in the generated schedule. Accordingly, the weekend workload of a nurse is between 5 and 7 shifts during the scheduling period. This leads to fairly assigning weekend shifts to the staff. The flexible arrangement of shifts is another advantage of the proposed timetable. This can help facilitate shift change between nurses. For example, Nurse 19 is considered for the morning shift on day 2 (given in table 8). If this nurse cannot be present in this shift, she can trade it with other allowed shifts of Nurse 20, because this nurse is off on day 2 and didn't work on the night shift of day 1 . Instead of this, nurse 19 has to be present on the morning shift of day 19 or the evening shift of Day 24 related to Nurse 20. Note that the shift change is done by agreement between the nurses and the consent of the head nurse.
Another factor that improves burnout and nurses' satisfaction is considering staff preferences in scheduling. In the generated timetable, most of the nurses' desires for work shifts and days off are applied. According to table 7, Nurse 19 prefers to be off on Day 25, and Nurse 16 wants to work the night shift on Day 7. As shown in table 8 , these preferences are accurately applied to the mentioned nurses. In this way, the preferences of other nurses are applied as much as possible. Note that some of the staff's preferences conflict with hospital rules and policies. Therefore, it is not possible to apply such cases when scheduling.

Figure 7 illustrates the percentage of applied nurses' preferences for work shifts and days off. Accordingly, for three nurses more than $60 \%$, six nurses more than $80 \%$, and other nurses $100 \%$ of these preferences have been applied. However, an average of $87 \%$ of nurses' preferences is assigned to them.


Fig 7. Status of applied preferences for nurses
In addition to the above, other assumptions intended for the case study have been observed in the generated schedule. In summary, the proposed mathematical model prepares a flexible and fair schedule to improve burnout and job satisfaction of nurses considering all assumptions and requirements of the problem.
In the following, the effect of the problem data on the model outputs is examined. In this process, the obtained solutions are analyzed for different values of a parameter. One of the factors that affect the arrangement of the generated timetable is the weight coefficients of the problem objectives. In the case study, these coefficients are determined based on the hospital management policy. Due to the significance of these weights in reaching the intended goals, the sensitivity analysis of the model is done based on these factors. Table 9 illustrated the results of this analysis. As shown in the table, the proposed model is solved for 10 different modes. In these cases, different values are defined for the factors. The results analysis states that decreasing the weight related to the term of nurses' shift preferences improves the optimal solution. In addition, the best value of the objective function is obtained when the weights of the terms related to days off preference and requested leave are at their greatest value. However, the definition of balanced values for the relevant coefficients provides an intermediate solution.

Table 9. Sensitivity analysis of the scheduling model based on
coefficients of the objective function

| Mode | Weight coefficients |  |  |  |
| :---: | :---: | :---: | :---: | :---: |
| $\begin{array}{ccccc}\hline \text { Working shifts } \\ \text { priorities }\end{array}$ | $\begin{array}{c}\omega 2 \\ \text { Days off } \\ \text { priorities }\end{array}$ | $\begin{array}{c}\omega 3 \\ \text { Results }\end{array}$ |  |  |
| Leave |  |  |  |  |
| allocation |  |  |  |  |$]$

In this section, the results of the nurses' scheduling model were investigated using real data. It was shown that the proposed model has the necessary validity and can be an efficient tool for scheduling of nurses in crises. The rules of seniority and job burnout were specially considered in this process. According to the results of interviews with nurses and hospital managers, it was found that these factors are very effective in improving the quality of healthcare services in crisis conditions. In addition, nurses admitted that paying attention to work preferences and limiting the number of undesirable shifts increased their satisfaction. The flexibility of the timetable against the unexpected absence of nurses was another advantage of the proposed model. Although the lack of human resources is inevitable in pandemic conditions, its consequences can be controlled with appropriate policies such as developing dynamic plans. Creating a fair schedule, paying attention to burnout factors, and taking necessary measures for the flexibility of schedules were among the parameters considered in this case study.
According to the results, the developed optimization problem was effectively implemented in the department under study. This model may be utilized according to the needs of other organizations and the necessity to improve the conditions caused by Covid-19 under the following conditions:

- The use of different grades of nursing, such as assistant nurse, auxiliary, multi-skilled nurses, etc., in addition to defining the seniority levels of nurses.
- All hospitals and healthcare centers that work in different shifts including two, three, or four shifts.
- Hospitals where the rules of seniority and productivity are a priority for them. Also, if these rules are not applied, the assumptions related to them can be ignored.


## 6- Conclusion

In this paper, an optimization problem was formulated for the nurses' scheduling focusing on burnout and job stress. In prior studies, different human factors were proposed to develop the NSP. Fatigue from long shifts, job stress caused by workload, and employee satisfaction considering personnel preferences were among the most important factors that were addressed in other optimization models. However, the development of nurse scheduling models based on the burnout factor was a gap that had not been addressed. In the presented model, the factors causing employee burnout along with its consequences were simultaneously considered. Increasing staff workload and assigning undesirable conditions to nurses during the outbreak of COVID-19 were considered factors affecting burnout. According to this, a new approach to define undesirable conditions in the optimization model was developed and it was tried that the allocation of these types of shifts to staff be limited. In addition, possible absences of nurses as one of the consequences of job burnout were controlled by a new formulation of the constraints related to shift change. In the formulated model, personnel were categorized based on seniority levels, and nurses' preferences for work shifts and days off were applied based on the weight of each category. Furthermore, the status of nurses' leave on the previous horizons to the fair allocation of the requested leaves to the staff was considered.
Due to the complexity of nurses' scheduling problems, the GA was used to solve the proposed problem. To assess the capability of this algorithm, the final solution of the model for 20 random samples was calculated by GA, PSO, and exact methods. The computational results evidenced that the GA was the most practical approach to solving this problem. This algorithm could generate quality outputs with an average gap of $0.22 \%$ in much less runtime compared to the exact method. Finally, this programming model was implemented in an actual case study in Iran to assess the sufficiency of the proposed process in real life. The generated schedule helped to control burnout and improve nurses' job satisfaction by maximizing nurses' preferences and limiting the allocation of undesirable conditions to staff.
In future studies, our proposed model can be extended by considering other factors that improve burnout such as limiting working hours per day, defining break time in working shifts, and controlling fatigue. In addition, the robustness of NSP against long-time absences, general defining of undesirable shifts, considering the burnout factor as an independent variable in the optimization model and balanced allocation of undesirable conditions to nurses are prominent research fields that can be addressed in future studies.

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