AMBULANCE ROUTING IN DISASTER RESPONSE CONSIDERING VARIABLE PATIENT CONDITION: NSGA-II AND MOPSO ALGORITHMS

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Abstract. The shortage of relief vehicles capacity is a common issue throughout disastrous situations due to the abundance of injured people who need urgent medical aid. Hence, ambulances fleet management is highly important to save as many injured individuals as possible. In this regard, the present paper defines different patient groups based on their needs and characteristics. In order to provide the affected people with proper and timely medical aid, changes in their health status are also considered. A Mixed-integer Linear Programming (MILP) model is proposed to find the best sequence of routes for each ambulance and minimize the latest service completion time (SCT) as well as the number of patients whose condition gets worse because of receiving untimely medical services. Non-dominated Sorting Genetic Algorithm II (NSGA-II) and Multi-Objective Particle Swarm Optimization (MOPSO) are used to find high-quality solutions over a short time. In the end, Lorestan province, Iran, is considered as a case study to assess the model’s performance and analyze the sensitivity of solutions with respect to the major parameters, which results in insightful managerial suggestions.

1. Introduction. Natural or human-made disasters can do severe damage to human life [24]. During such catastrophic situations, efficient logistics operations can alleviate the damage severity to a great extent. It is recognized that the majority of victims perish due to receiving untimely medical aid [40]. Therefore, it is crucial to devise a plan that assigns logistic relief vehicles as quickly and efficiently as possible [4, 43]. However, a few studies have addressed the application of Vehicle Routing Problem (VRP) in disaster response [33].

This paper aims to solve an Ambulance Routing Problem (ARP) for the post-disaster phase. Ambulances are in charge of carrying medical staff and injured people between incident centers and hospitals. One of the most challenging constraints in such a problem is the noticeable rise in medical demands after the disaster, which necessitates the efficient use of available ambulances over a limited response time [26].
In this study, patients are categorized into three groups, each of which are treated differently based on their needs:

- **Red Code (RC) patients**: seriously-injured people who are in urgent need of help. Thus, they should be taken to the nearest hospital by an ambulance as soon as possible. In the case of being visited after a particular time threshold, they may perish.

- **Green Code (GC) patients**: slightly-injured people who need to receive first aid in the incident field. If ambulances arrive at the incident field after a specific time threshold, they may turn to RC patients.

- **Dead patients**: people who have perished owing to receiving medical services too late. In this case, ambulances must pass over them to save the injured people who are still alive.

Fig. 1 demonstrates patients’ grouping as well as the process through which their health status changes. The main difference between this triage and civil healthcare is that it aims to save a large number of people using limited ambulances as efficiently as possible.

**Figure 1.** Requests classification and changes in patient condition.
It is assumed that each ambulance can pick up only one RC patient at a time and carry the patient directly to the nearest hospital considering the hospital capacity limitation. Ambulances can visit multiple GC patients before approaching the first RC patient who needs to be transferred to a hospital. The origin and destination of each ambulance may be different or the same.

The present study aims to formulate a mathematical model that takes changes in patients’ conditions into account. Although this assumption significantly improves the model’s real-world application, it has never been studied by the previous works. Considering variable patient condition and different patient groups enhance the management of limited resources, including hospitals, ambulances, and time during the post-disaster phase, which makes an undeniable contribution to reducing the number of casualties.

2. Literature review. During the last decade, many researchers have used operations research techniques to improve logistics associated with different problems, e.g., water distribution, energy and sustainable supply chain [21, 20, 34]. In health-care problems, there has been an growing interest in studies known as Emergency Medical Service (EMS) [3]. These studies can be categorized based on various factors. One of these factors is the aim of the applied objective function. For example, Schuurman et al. [37] developed a model to determine the optimal site for an expanded Helicopter Emergency Medical Service (HEMS) to save a great number of injured people. Also, Erdemir et al. [12] focused on maximizing demand coverage and minimization of establishment cost related to three coverage options, including ground EMS, air EMS, and a combination of these two. Branas et al. [7] employed integer and heuristic programming to decrease trauma patients’ response time so that fewer people would perish. The mentioned response time can be defined as the sum of the travel time from the relief vehicle depot to the injury scene and the travel time from the injury scene to the closest medical center. Furuta and Tanaka [14] used a bi-objective integer programming model in which the second objective function is in charge of minimizing the maximum transportation time. To evaluate the suggested model’s efficiency, they considered a real case study in Japan using geographical and population data to acquire promising results.

A wide variety of solution methods have been utilized in previous studies. From the exact methodologies perspective, Sasaki et al. [35] proposed a straightforward enumeration-based approach to solve a bi-level mathematical model. The first level determines transfer points, while the second level dedicates an adequate location to each facility in the network. Although this solution method obtains exact optimal solutions, it fails to find an answer for a 200-node problem even after ten hours.

Despite acquiring high-quality solutions, exact methods can be significantly time-consuming for real-world applications, especially during the post-disaster phase, when wasting the slightest amount of time threatens many people’s lives. Therefore, many studies turned to semi-exact, heuristic, and metaheuristic algorithms with shorter computational times. Berman et al. [5] investigated the location of a central facility (such as a hospital) and several transfer nodes that perform as collector points for customers who demand emergency services. Three heuristics, including Decent Approach (DA), Simulated Annealing (SA), and Tabu Search (TS) were employed as the solution methods. SA outperforms the other heuristics in finding the best-known solution for all 40 test instances, while DA is the
fastest methodology as it solves problems with 900 nodes in about 77 seconds. Hosseiniouj and Bashiri [25] studied a stochastic transfer point location problem with weighted demand points. They used an analytical/numerical approach resulting in approximate optimal solutions with relative average errors of 4% and 1.6%. This methodology can solve problems with 500 demand points over less than six seconds. Other methods for similar problems have been employed in Kalantari et al. [27], Camacho et al. [8], and Tirkolaece et al. [42].

In addition, solution methods suggested by Garg [16] and Garg [17] can be applied to solve a wide range of constrained optimization problems. More practical algorithms are also available in Garg and Sharma [18], Garg [15], and Patwal et al. [32].

Investigating patient groups has been taught as a critical factor in previous studies. This system classifies and prioritizes injured people according to the severity of the injuries during a short period, which helps relief staff to save time and medical resources, especially during mass-victim disasters. Talarico et al. [40] divided patients into two groups, namely slightly-injured and seriously-injured individuals. The former group can be assisted directly in the disaster site, while the latter group needs to be taken to a hospital where more specialized medical facilities are available. Likewise, Tikani and Setak [41] assumed three types of patients; GC patients, yellow code patients, and RC patients. Both the yellow code and RC patients are required to be transferred to hospitals; however, the assigned ambulances to the last group have to be equipped with some life-support medical equipment.

Locating, dispatching, and routing problems cover a significant share of EMS studies. From the locating problem perspective, it makes an effort to distribute ambulances adequately throughout a specific geographical area so that response time to emergency demands will not transcend a certain threshold [13]. In a dynamic ambulance location problem, a number of available ambulances are already assigned to disaster fields, which necessitates relocation of some idle relief vehicles for bridging the coverage gap [19]. The main objective of the ambulance location problem presented by Knight et al. [28] is to determine ambulance locations in a way that the survival probability is maximized. In their study, patients have diverse medical status as well as target response time.

Considering the dispatching problem, it aims to assign the incoming medical demands to the ambulances, which is usually integrated with the locating problem. Toro-Díaz et al. [45] employed such a combinatorial mathematical model to investigate the effect of patients’ queue on coverage and response time, especially when server systems are noticeably-congested. Andersson and Värbrand [1] considered the urgency of the medical demand and ambulance closeness to the incident site as two of the main factors that affect the dispatching part of the combinatorial model. In a similar study, Schmid [36] combined relocation and dispatching and used approximate dynamic programming to decrease the expected total response time.

In routing problems, finding the shortest way plays a key role in traffic conditions and road damage [26, 23]. Tlili et al. [44] proposed a genetic-based algorithm for solving an ambulatory fleet routing problem in times of disaster while simultaneously assisting two patient groups with different injury severities.

Regarding the recent studies in the EMS field, various transfer modes can be presumed for transferring patients from incident sites to medical centers. Bozorgi-Amiri et al. [6] defined three transfer modes to provide medical aid for injured
people of a region that lacks ground relief coverage. In the first mode, ambulances directly transfer patients from the demand areas to the hospital. In the second mode, patients are taken to the helicopter station to be transferred to the hospital. In the last mode, patients are transferred to the helipads and then a helicopter is in charge of taking them to the hospital. The purpose of the mentioned study is to find the optimal location for helipads and helicopter stations while taking uncertain demand areas into account. Other related works can be found in Navazi et al. [30], Özdamar and Ertem [31], and Zheng et al. [46].

According to the shortcomings in the literature, the main contributions of this paper are as follows:

1. Defining three different patient groups based on various injury severities and vital signs so that the appropriate relief measures can be taken accordingly.
2. Considering a time threshold for each patient group to take changes in patients’ health status into account, which in turn improves the management of limited resources (i.e. hospitals, ambulances, and time) and leads to the reduction of casualties in disaster times.
3. Due to the proposed problem’s NP-hardness, two metaheuristic methods, including NSGA-II and MOPSO are utilized to solve the concerned problem efficiently. Also, the performance of both algorithms is assessed from different aspects.
4. Implementing the model in Lorestan province, Iran, as a real case study to evaluate its performance, analyze the influence of the structural parameters on the obtained solutions, and finally, infer some enlightening managerial insights.

The rest of this paper is structured as follows. In the next section, different aspects of the studied system are defined in detail. In Section 3, the problem is formulated as a Mixed-integer Linear Programming (MILP) model with a description of the employed parameters, variables, and constraints. Section 4 presents a summarized report of the proposed solution methods. Section 5 is dedicated to the evaluation of the proposed algorithms using different test instances. Moreover, this section focuses on a real case study to carry out a comprehensive sensitivity analysis of the suggested model’s major parameters. Eventually, the last section includes some conclusions and a number of suggestions as future perspectives.

| Authors | Objective function | Problem | Modes | Variable condition | Patient group | Solution approach |
|---------|--------------------|---------|-------|-------------------|---------------|------------------|
| Talarico et al. [40] | Min max response time | Routing | - | - | X | Heuristic |
| Jothi et al. [15] | Min demand coverage/Min coverage cost | Routing | - | - | X | Heuristic |
| Silvanini et al. [45] | Max demand coverage | Locating | X | - | - | Exact |
| Eckner et al. [5] | Min establishment cost/Max demand coverage | Locating | X | - | - | Heuristic |
| Brune et al. [7] | Min average response time | Locating | X | - | - | Heuristic |
| Furesi and Tanda [34] | Min max response time/Min response time | Locating | X | - | - | Exact |
| Sood et al. [33] | Min transfer time | Location | - | - | - | Heuristic |
| Berman et al. [13] | Min transfer time | Location | - | - | - | Heuristic |
| Rosas-Jimenez and Balakrishnan [25] | Min max distance | Location | - | - | - | Exact/analytical/numerical |
| Kalantari et al. [27] | Min transfer time | Location | X | - | - | Exact |
| Camacho et al. [4] | Min response time | Distribution | X | - | - | Exact |
| Tóth and Steel [43] | Min max response time | Routing | - | - | X | Heuristic |
| Fitzenreiter and Sjöberg [18] | Min max response time | Location | - | - | X | Heuristic |
| Gudmundsson et al. [19] | Max demand coverage | Relocating | - | - | - | Heuristic |
| Knight et al. [26] | Min max travel time | Location | - | - | - | Heuristic |
| Toh-Saku et al. [42] | Min response time/Max demand coverage | Location/Depot | - | - | - | Exact |
| Andersen and Vahabzadeh [20] | Min transfer time | Location/Depot | - | - | - | Heuristic |
| Schmid [24] | Min average response time | Relocating/Depot | - | - | - | Heuristic |
| Goldberg and Latimore [29] | Min travel cost | Routing | - | - | - | Service |
| Tóth et al. [44] | Min travel cost | Routing | - | - | - | Heuristic |
| Buning and Amiri [39] | Min max response time | Location | X | - | - | Exact |
| Novet et al. [38] | Min establishment cost/Min response time | Location | X | - | - | Exact |
| The paper | Min max response time/Min number of patients | Routing | X | X | X | Heuristic |
3. Problem description.

3.1. ARP. The applied notations in problem formulation are shown in Table 2. The purpose of ARP is to allocate adequate routes to a fleet of ambulances in set \( k \in K \) that are in charge of giving aid to patients. Let \( P = G \cup R \) signify the set of patients that consists of two patient groups, namely GC patients \( G \) and RC patients \( R \). GC patients receive first aid in the field. In contrast, RC patients are required to be directly transferred to available hospitals in set \( h \in H \). Based on the defined sets, \( N = G \cup R \cup H \) represents all of the nodes comprising the network. A binary parameter \( l_k^h \) indicates the initial location of each ambulance. Each ambulance starts the travel from its initial location and finishes it at any hospital. Besides, \( A = \{P \times P\} \cup \{P \times H\} \cup \{H \times P\} \) demonstrates the set of connected arcs where \( t(i, j) \) is the travel time related to arc \((i, j) \in A\).

A service duration \( s_i \) is associated with each patient. This parameter denotes the time needed to prepare an RC patient for transportation to a hospital, whereas for GC patients, it determines the time required to provide them with first aid in the field. Since dropping off patients at hospitals also takes a while, a parameter \( s_h \) is applied to consider this period. A capacity \( cap_h \) is considered for each hospital, limiting the number of patients assigned to a hospital. It is presumed that the total hospitals capacity is sufficient to fulfill all of the requests related to RC patients. Furthermore, each ambulance can carry only one RC patient during its direct travel to the nearest hospital that is not fully occupied. On the contrary, in the case of visiting a GC patient, the ambulance can move towards the next patient who may have a green or red status.

Three binary variables \( xg_i \), \( xr_i \), and \( xd_i \) are used to determine the condition of each patient \( i \in P \) through the planning period. A patients’ condition can be green, red, or perished. In order to take all RC patients to hospitals regardless of their initial condition, the ambulances must pass over the perished ones. Other employed parameters and variables are described in Table 2.

SCT and time threshold concepts are applied to improve the quality of the solutions. SCT is defined to denote the time when an RC patient is dropped off at a hospital, while for a GC patient, it is the time of first aid termination. The first suggested objective function aims to minimize the weighted sum of the latest SCT \( Tg \) between all GC patients and the latest SCT \( Tr \) between all RC patients. A planner can use weights \( wg \) and \( wr \) to determine the relative priority of patient groups over each other. Secondly, a time threshold is allocated to each patient group. When \( a_i \) that is the visiting time of patient \( i \in G \) exceeds the time threshold \( mg \), the patient turns to an RC patient, which turns \( xg_i \) to 0 and \( xr_i \) to 1. Likewise, if \( a_i \) exceeds the time threshold \( mr \) for patient \( i \in R \), the patient perishes that makes \( xr_i \) equal to 0 and \( xd_i \) equal to 1. The second objective function is inclined to minimize the number of patients whose condition gets more critical due to not receiving timely medical aid.

Given the mentioned assumptions, the model described in the following subsection differs from the existing literature.

3.2. Mathematical formulation. The following mathematical formulation is proposed to model the above-discussed routing problem:

\[
Min f_1 = wg \times Tg + wr \times Tr
\]
Table 2. Employed notation for modeling the ARP.

| Sets:                  |                                                   |
|-----------------------|--------------------------------------------------|
| $R$                   | RC patients                                      |
| $G$                   | GC patients                                      |
| $P$                   | All of the patients in the network, $P = G \cup R$|
| $H$                   | Hospitals                                         |
| $N$                   | All of the nodes in the network, $N = G \cup R \cup H$|
| $K$                   | Ambulances                                        |
| $A$                   | Connected area, $A = (P \times P) \cup (P \times H) \cup (H \times P)$|

| Parameters:           |                                                   |
|-----------------------|--------------------------------------------------|
| $i_h^k$               | Binary parameter, 1 if hospital $h$ is the initial location of the ambulance $k$ |
| $t_{ij}$              | Travel time on arc $(i,j) \in A$                  |
| $s_i$                 | Service duration of patient $i \in P$            |
| $s_h$                 | The amount of time needed to drop off an RC patient at hospital $h \in H$ |
| $cap_h$               | Hospital $h \in H$ capacity                      |
| $wg$                  | Priority of GC patients                          |
| $wr$                  | Priority of RC patients                          |
| $mg$                  | Maximum time that a GC patient’s condition remains green |
| $mr$                  | Maximum time that an RC patient’s condition remains red |
| $pr$                  | Penalty per each increase in the number of RC patients |
| $pd$                  | Penalty per each increase in the number of perished patients |

| Decision Variables:   |                                                   |
|-----------------------|--------------------------------------------------|
| $x_{ij}^k$            | Binary variable, 1 if ambulance $k$ visits patient $j$ after patient $i$ |
| $y_{ih}$              | Binary variable, 1 if hospital $h$ is assigned to RC patient $i$ |
| $a_i$                 | The time when patient $i \in P$ is visited       |
| $Tg$                  | Latest SCT between all GC patients               |
| $Tr$                  | Latest SCT between all RC patients               |
| $xg_i$                | Binary variable, 1 if patient $i \in P$ has a green condition when it is visited by an ambulance |
| $xr_i$                | Binary variable, 1 if patient $i \in P$ has a red condition when it is visited by an ambulance |
| $xd_i$                | Binary variable, 1 if patient $i \in P$ is perished when it is visited by an ambulance |

\[
\begin{align*}
    Min f_2 & = \sum_{i \in P} x_{r_i} \times pr + \sum_{i \in P} x_{d_i} \times pd \\
    \sum_{j \in N} x_{hj}^k & = l_h^k \quad \forall h \in H; k \in K \\
    \sum_{k \in K} \sum_{j \in N} x_{ji}^k & = 1 \quad \forall i \in P
\end{align*}
\]
\[ \sum_{j \in N} x_{ji}^k = \sum_{j \in N} x_{ij}^k \quad \forall \; i \in P; \; k \in K \] (5)

\[ \sum_{i \in P} y_{ih} \leq \text{cap}_h \quad \forall \; h \in H \] (6)

\[ a_i + s_i + t_{ij} \leq a_j + (1 - \sum_{k \in K} x_{ij}^k).M \quad \forall \; xg_i = 1; \; i, j \in P \] (7)

\[ a_h + s_h + t_{hj} \leq a_j + (1 - \sum_{k \in K} x_{hj}^k).M \quad \forall \; j \in P \] (8)

\[ a_i + s_i + t_{ih} + s_h + t_{hj} \leq a_j + (2 - \sum_{k \in K} x_{ih}^k - y_{ih}).M \quad \forall \; xr_i = 1; \; i, j \in P; \; h \in H \] (9)

\[ a_i + t_{ij} \leq a_j + (1 - \sum_{k \in K} x_{ij}^k).M \quad \forall \; xd_i = 1; \; i, j \in P \] (10)

\[ \sum_{k \in K} x_{ih}^k = y_{ih} \quad \forall \; i \in P; \; h \in H \] (11)

\[ \sum_{k \in K} \sum_{h \in H} x_{ih}^k = xd_i \quad \forall \; i \in P \] (12)

\[ \sum_{k \in K} \sum_{h \in H} x_{ih}^k = 1 - xd_i \quad \forall \; i \in P \] (13)

\[ Tg \geq a_i + s_i \quad \forall \; xg_i = 1; \; i \in P \] (14)

\[ Tr \geq a_i + s_i + (t_{ih} + s_h).y_{ih} \quad \forall \; xr_i = 1; \; i \in P; \; h \in H \] (15)

\[ xg_i + xr_i + xd_i = 1 \quad \forall \; i \in P \] (16)

\[ \begin{cases} 
if \; a_i \leq mg \rightarrow xg_i = 1 \\
if \; mg \leq a_i \leq mg + mr \rightarrow xr_i = 1 \quad \forall \; i \in G \\
if \; a_i \geq mg + mr \rightarrow xd_i = 1 
\end{cases} \] (17)

\[ \begin{cases} 
if \; a_i \leq mr \rightarrow xr_i = 1 \\
if \; a_i \geq mr \rightarrow xd_i = 1 \quad \forall \; i \in G 
\end{cases} \] (18)

\[ a_i \geq 0 \quad \forall \; i \in N \]

\[ y_{ih}, x_{ij}^k \in \{0, 1\} \quad \forall \; (i, j) \in A; \; k \in K; \; h \in H \] (19)
The role of the objective function (1) is to minimize the weighted combination of the latest SCT among GC and RC patients, while the objective function (2) tends to minimize the number of RC and perished patients during the given time interval. Constraint (3) enforces that ambulances start traveling from their origin hospitals. Based on constraint (4), ambulances have to visit all GC and RC patients exactly once. Constraint (5) ensures that ambulances need to leave the patient’s location after performing the visit and finish their travel by going to one of the hospitals. Hospitals capacity limit is respected by constraint (6). Constraints (7)-(10) control ambulances’ arrival time to the patients’ locations. As constraints (7) and (8) suggest, the arrival time \( a_j \) of an ambulance at patient \( j \) depends on the arrival time of the ambulance at the previous node that represents a GC patient or a hospital, its service duration \( s_i \), and the travel time \( t_{ij} \) to go from \( i \) to \( j \). Constraint (9) ensures that if the previous node denotes an RC patient \( i \), travel time \( t_{ih} \) to go from \( i \) to the assigned hospital and transfer time to the hospital have to be considered as well. Ambulances are not allowed to stop by patients who have perished owing to receiving overly-late medical aid and are required to move directly towards the next patient. As a result, if the previous node \( i \) signifies a perished patient, only \( a_i \) and \( t_{ij} \) are taken into account for determining \( a_j \), which is enforced by constraint (10). Constraint (11) coordinates the routing variable from the patient’s location to the assigned hospital \( x_{ih} \) with the patient-to-hospital assignment variable \( y_{ih} \). Based on constraints (12) and (13), only RC patients must be delivered to hospitals, while perished ones are not allowed. The latest SCT amongst GC and RC patients is determined by constraints (14) and (15), respectively. Constraint (16) ensures that being visited by an ambulance, a patient can be GC, RC, or perished. The role of time thresholds in changing a patient’s condition can be seen throughout constraints (17) and (18). These two constraints are shown in the form of mathematical inequalities in Appendix A. In the end, the range of the decision variables is stated by constraint (19).

4. Solution approach. The present problem has \( P^2K + 5P + RH + G \) binary decision variables and \( P^3(H + 2) + P^2(H + 1) + P(2H + K + 10) + KH + 3G + N \) constraints, where \( P, K, R, H, G, \) and \( N \) are assumed the sizes of the aforementioned sets. Since VRP is an NP-hard problem, the proposed model which has more binary variables and constraints in comparison to VRP, is strongly NP-hard. Consequently, the NP-hard and bi-objective nature of the model necessitates the use of multi-objective metaheuristic solution methods for this study. One of the most important advantages of employing metaheuristic algorithms is solving large-scale problems over an adequate amount of time [47]. As a result, two of the most famous multi-objective metaheuristics, namely NSGA-II and MOPSO algorithms are applied for solving the problem [38, 9].

4.1. Proposed NSGA-II. NSGA-II was introduced by Deb et al. [10] for the first time. This algorithm can be considered as an extension of the Genetic Algorithm (GA) with the same operators (crossover and mutation) that can handle mathematical models with multiple contradicting objective functions. The flowchart of the algorithm is presented in Fig. 2, which is remarkably similar to that of GA. Based on the flowchart, the algorithm starts with \( N_{pop} \) number of individuals as the initial population that is randomly generated. Next, non-dominated sorting is used to divide the initial population into several Pareto fronts. Each front consists of non-dominated individuals that need to be sorted according to the crowding distance
operator. This operator is responsible for measuring the density of possible solutions along with a particular solution approximately. Then, roulette wheel selection is employed to choose a number of parents that undertake crossover and mutation for forming offspring population. In this type of selection, individuals with better rank and more crowding distance have a higher chance of being chosen. The next generation consists of the best population members among the previous generation members and offspring, considering the non-dominated sorting and crowding distance in each front. The algorithm stops when the maximum number of iterations is met. First-ranked individuals among the last generation form the Pareto optimal solution of the proposed algorithm.

4.1.1. Chromosome representation. Chromosomes are individuals in genetic-based algorithms, each of which represents an encoded solution of the problem. According to the study of Tikani and Setak [41], the applied chromosome for the discussed routing problem is a string of integer numbers with the length of $N$. $N$ is the number of patients added by a number of zeros that play the role of the separators. Fig. 3 is an example of an encoded chromosome and its decoded form with eight patients. Patients number 3, 2, and 5 are RC patients who need to be taken to one of the hospitals 1 and 2, while patient number 8 is dead and must be passed over by the assigned ambulance. In each string, the zeros separate the route of the ambulances. It has to be noted that each ambulance’s initial location determines the start point of its route. Other mentioned constraints in Section 3 are defined in the form of highly-penalized violations for the algorithm.

4.1.2. Crossover operator. In the crossover operator, two chromosomes are chosen as parents to form the offspring after mating. As mentioned before, the proposed selection method in this study is the roulette wheel selection method, which propels the algorithm to choose chromosomes with better rank and more crowding distance. Among different methods employed in terms of parents’ combination in routing problems, classical order crossover is used to create two offspring per each mate. Based on the study of Tikani and Setak [41], the steps of the classical order crossover are as follows:

- Step 1: Eliminate the genes with zero value from each parent chromosome.
- Step 2: Select a subset of genes from the parent number 1 randomly.
- Step 3: Create an offspring by placing the subset of genes into the related positions in the offspring.
- Step 4: Eliminate selected genes in Step 2 from parent number 2. The remainder subset determines the sequence of other nodes.
- Step 5: Place the genes into the offspring’s vacant positions from left to right by not changing the sequence of genes, based on Step 4. Replace the separator zeros in the offspring same as the selected parent in Step2.
- Step 6: Repeat steps 1 to 5 by using the parent number 2 to create the second offspring.

4.1.3. Mutation operator. The mutation operator prevents local optimum answers by inserting random exchanges to the chromosomes for creating new individuals. Among diverse mutation operators, the two-point swap operator is proposed in this study. Two-point swap operator randomly selects two genes in the chromosome and exchanges their locations. The mentioned crossover and mutation operators are illustrated in Figures 4 and 5.
4.2. Proposed MOPSO. MOPSO is a metaheuristic algorithm based on the intelligence group introduced by Coello et al. [23] for the first time. The detailed flowchart of MOPSO can be seen in Fig. 6. In this algorithm, each solution is considered as a particle that tries to update its velocity $v_p$ and its position $x_p$ at iteration $t$ based on two categories of information, namely its previous best experience $x_{p_{i,best}}$ and the best global experience throughout the whole swarm $x_{g_{best}}$. Equations (20) and (21) show the mathematical formulation of the updating procedure.
Figure 3. An illustrative example of the decoding process.

Figure 4. An illustrative example of the classical order crossover.
Figure 5. An illustrative example of the two-point swap mutation.

\[ v_p(t) = w.v_p(t - 1) + c_1.r_1.(x_{pb}(t) - x_p(t)) + c_2.r_2.(x_g(t) - x_p(t)) \] (20)

\[ x_p(t) = x_p(t - 1) + v_p(t) \] (21)

\( v \) denotes the inertia factor that affects the global and local ability of the particle. \( c_1 \) is the cognitive coefficient that influences the impact of \( x_{pb} \), whereas \( c_2 \) is the social learning coefficient that is responsible for controlling influences the effect of \( x_g \).

5. Computational results. This section compares the results of the applied meta-heuristic algorithms using instances of different scales. The efficiency and reliability of metaheuristic approaches are highly affected by their parameters. Hence, parameter calibration is necessary before comparing the results of various algorithms [11]. Here, the Taguchi method is used for setting the parameters of the algorithms. Afterward, the results of the algorithms are compared based on numerical examples.

In this research, each ambulance randomly starts its travel from a hospital. Moreover, \( t_{ij} \) is uniformly distributed within the interval \([0.25, 2.5]\) for \( i, j \in N \), while \( s_i \) and \( s_h \) follow the normal distribution with mean 0.3 and 0.16 of an hour and standard deviation 0.1 and 0.08, respectively. Also, \( cap_h \) can take any integer value between one to five with equal probabilities. Furthermore, \( mg, mr, pr, pd, wg, \) and \( wr \) equal to 60, 30, 200, 32, 0.4, and 0.6, respectively.

5.1. Parameter tuning. In metaheuristic algorithms, the Taguchi method is a powerful means for finding suitable parameter values [39]. Here, a three-level Taguchi method is employed to tune NSGA-II parameters, including population size \( N_{pop} \), maximum number of iterations \( max - it \), crossover rate \( p_c \), and mutation rate \( p_m \) for different problem scales. The Taguchi method uses the best value of each objective function as the assessment criterion to dedicate proper values to the parameters. In Fig. 7, the Taguchi method outcomes for the 10th test instance are drawn with Minitab software. In addition, MOPSO tuned parameters, such as the optimal level of swarm size \( N_{pop} \), maximum number of iterations \( max - it \), repository size \( N_r \), inertia weight \( w \), personal learning coefficient \( c_1 \), and global learning coefficient \( c_2 \) can be seen in Fig. 8. Table 3 reports the best values for the parameters of the proposed solution methods.

| Algorithm | \( N_{pop} \) | \( max - it \) | \( p_c \) | \( p_m \) | \( p_m \) | \( w \) | \( c_1 \) | \( c_2 \) |
|-----------|---------------|----------------|--------|--------|--------|-------|-------|-------|
| NSGA-II   | 75            | 100            | 0.6    | 0.2    | -      | -     | -     | -     |
| MOPSO     | 100           | 125            | -      | -      | 75     | 0.5   | 1.25  | 1.5   |

Table 3. Adjusted parameters for NSGA-II and MOPSO.
5.2. Model validation. Test instance 1, which is a small-scale problem, is solved by AUGMECON2 method in GAMS software, version 24.1.2, using CPLEX solver to check the validity of the suggested mathematical model. AUGMECON2 is one of the most famous exact algorithms to solve multi-objective problems provided by Mavrotas and Florios [29]. Comparing to the epsilon-constraint method, AUGMECON2 takes advantage of the lexicographic optimization procedure in producing a pay-off table, which leads to an effective generation of Pareto optimal solutions [22, 2]. It should be noted that test instance 1 is completely hypothetical and may have no grounding in real-world case studies.
A vector \( (H, A, G, R) \) is used to demonstrate the dimension of each test instance. The vector denotes the number of hospitals, the number of ambulances, and the number of GC and RC patients, respectively. In test instance 1, a fleet of four ambulances \((a_1 \text{ to } a_4)\) is available to provide seven patients, consisting of four GC and three RC patients \((g_1 \text{ to } g_4, r_1 \text{ to } r_3)\) with medical aid. Each RC patient has to be carried to one of the three hospitals \((h_1 \text{ to } h_3)\) in the network, which have a predetermined capacity. The resulting Pareto optimal solutions that confirm the conflict between the proposed objective functions are depicted in Fig. 9.
In order to evaluate the efficiency of the proposed solution methods, 14 test instances with various dimensions are randomly generated by the coded instance generator of MATLAB R2016b software. Both NSGA-II and MOPSO algorithms are implemented in MATLAB software and executed on an Intel Corei5 PC with 6 GB of RAM and more than 1 GHz CPU without any parallel computing options. Test instances are conducted independently for about ten times and the averaged results are compared to evaluate the quality of the proposed solution approaches. For test instance 10, the Pareto optimal solutions of the solution approaches are given in Fig. 10.

5.3. Comparison metrics. The performance of multi-objective metaheuristic algorithms can be assessed by numerous comparison metrics. Here, the following evaluation criteria are applied to compare the performance of the proposed algorithm:

- CPU time
- Ratio of non-dominated individuals (RNI)
- Diversity metric (DM)
- Spacing metric (SM)
- Generational distance (GD)

CPU time refers to the time during which an algorithm is implemented. RNI can be considered as a quantitative metric that calculates the ratio of the number of Pareto optimal solutions to the population size by using the following equation:

$$\text{RNI} = \frac{|\mathcal{F}|}{N_{\text{pop}}}$$  \hspace{1cm} (22)

The higher RNI an algorithm has, the more efficient it is. DM provides information about the breadth of non-dominated solutions based on Equation (23), where
Figure 10. Pareto front approximation for test instance 10.

$N$ is the number of Pareto optimal solutions and $\max \|x^k_i - y^k_i\|$ denotes the maximum Euclidean distance between non-dominated solutions. Higher values of this metric are more desirable as they indicate the coverage of larger solution spaces.

$$DM = \sqrt{\sum_{i=1}^{N} \max \|x^k_i - y^k_i\|}$$  \hspace{1cm} (23)

SM uses Equations (24) and (25) to determine the dispersion of non-dominated solutions throughout the resulting Pareto front, where $d_i$ is the minimum distance of Pareto optimal solution $i$ from other Pareto fronts, $\bar{d}$ is the averaged non-dominated solution, and $f^k_i$ is the value of the objective function $k$ for Pareto optimal solution $i$.

$$SM = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (d_i - \bar{d})^2}$$  \hspace{1cm} (24)

$$d_i = \min_{k=1}^{K} |f^k_j - f^k_i| \quad \forall \ i, j \in 1, ..., N; i \neq j$$  \hspace{1cm} (25)

In contrast to the other mentioned metrics, the lower value of SM is better cause it shows a uniform distribution of the optimal Pareto solutions. GD evaluates how close are the solutions to the real Pareto front by employing Equation (26). Lower levels of GD indicate the acceptable performance of an algorithm.

$$GD = \sqrt{\frac{\sum_{i=1}^{N} d_i^2}{N}}$$  \hspace{1cm} (26)
The computational results, related to the comparison of NSGA-II and MOPSO performance in the studied problem, are reported in Figures 11-15. More details of this comparison are available in Table 4. Finally, the applied algorithms are compared regarding the mentioned metrics by taking advantage of the two-sample t-test. Table 5 presents the results of these comparisons.

According to the conducted comparison, NSGA-II performs better than MOPSO in terms of RNI and SM metrics, which means it results in more non-dominated solutions with more uniformity in the solution space. Moreover, answers obtained by NSGA-II are more reliable regarding GD metric. On the other hand, MOPSO is superior to NSGA-II when it comes to the diversity of the Pareto solutions assessed by DM metric. As the p-value in the statistical evaluation reveals, the means of the CPU times are negligibly different between the proposed algorithms, which is because NSGA-II and MOPSO have a relatively similar performance in small-scale problems. At the same time, NSGA-II outdoes MOPSO gradually as the dimension of the problem increases.

![Figure 11. Comparison of NSGA-II and MOPSO based on CPU time.](image)

**Table 4.** Results of the 15 problem instances using NSGA-II and MOPSO.

| Problem Num. | Dimension | NSGA-II | MOPSO | Optimal CPU time (s) |
|--------------|-----------|---------|-------|----------------------|
| 1            | (3,4,4,3) | 124.23  | 0.31  | 2.1253               |
| 2            | (5,6,8,4) | 152.4   | 0.37  | 1.5301               |
| 3            | (8,10,10,7) | 139.87 | 0.29  | 1.2964               |
| 4            | (12,15,11,11) | 140.12 | 0.4   | 4.374               |
| 5            | (15,17,13,13) | 156.76 | 0.64  | 1.5964               |
| 6            | (20,23,18,18) | 161.2  | 0.57  | 1.4894               |
| 7            | (20,24,22,22) | 168.94 | 0.59  | 1.9442               |
| 8            | (25,28,21,20) | 175.54 | 0.21  | 2.3537               |
| 9            | (25,27,25,21) | 179.36 | 0.28  | 3.341               |
| 10           | (30,32,24,22) | 186.87 | 0.98  | 3.7609               |
| 11           | (40,43,29,25) | 194.3  | 0.93  | 3.2745               |
| 12           | (50,55,41,32) | 212.25 | 0.73  | 2.8954               |
| 13           | (75,83,66,45) | 237.86 | 0.77  | 5.762               |
| 14           | (90,95,70,51) | 264.22 | 0.86  | 3.8713               |
| 15           | (100,112,84,62) | 283.67 | 0.94  | 1.8751               |
Table 5. The analytical results of two-sample t-test.

| Criteria | Optimal method | Average results | Two-sample t-test | P-value |
|----------|----------------|-----------------|------------------|---------|
| CPU time (s) | Both methods | 194.5727 | 205.6213 | $\mu_{\text{NSGA-II}} = \mu_{\text{MOPSO}}$ | 0 |
| RNI | NSGA-II | 0.5833 | 0.4326 | $\mu_{\text{NSGA-II}} > \mu_{\text{MOPSO}}$ | 0.32 |
| DM | MOPSO | 2.6276 | 3.8711 | $\mu_{\text{NSGA-II}} < \mu_{\text{MOPSO}}$ | 0.212 |
| SM | NSGA-II | 0.0079 | 0.0098 | $\mu_{\text{NSGA-II}} < \mu_{\text{MOPSO}}$ | 0.901 |
| GD | NSGA-II | 0.0036 | 0.0048 | $\mu_{\text{NSGA-II}} < \mu_{\text{MOPSO}}$ | 0.625 |

Fig. 12. Comparison of NSGA-II and MOPSO based on RNI.

Fig. 13. Comparison of NSGA-II and MOPSO based on DM.

5.4. Case study. Lorestan, which is one of the most disaster-prone provinces by being in danger of flooding and earthquakes, is located in the west of Iran with an
approximate area of 28300 km\(^2\) and over 1.7 million populations. Table 6 lists the most important cities in the province according to their population and the expected crisis severity in times of disaster. In this study, the required practical data were acquired using GIS software as well as historical and statistical data provided by the national disaster management organization of Iran.
Fig. 16 demonstrates the listed cities that resemble potential locations for medical demand and the available hospitals in the network. Other essential data related to the hospitals are reported in Table 7.

### Table 6. Data related to the Lorestan province cities.

| City name     | Population | % of injured people | % of GC demands | % of RC demands |
|---------------|------------|---------------------|-----------------|-----------------|
| Aleshtar      | 33,132     | 30%                 | 88%             | 12%             |
| Aligudarz     | 89,521     | 21%                 | 49%             | 51%             |
| Azna          | 41,703     | 27%                 | 83%             | 17%             |
| Borujerd      | 245,730    | 19%                 | 77%             | 23%             |
| Dorud         | 100,979    | 32%                 | 66%             | 34%             |
| Khorramabad   | 354,854    | 15%                 | 41%             | 59%             |
| Kuhdasht      | 111,737    | 28%                 | 58%             | 42%             |
| Nur Abad      | 62,195     | 34%                 | 71%             | 29%             |
| Pol Dokhtar   | 32,590     | 26%                 | 92%             | 8%              |

### Table 7. Data related to the Lorestan province hospitals.

| Hospital name          | RC patient capacity | Number of ambulances |
|------------------------|---------------------|----------------------|
| Ibn Sina               | 120                 | 25                   |
| Imam Ali               | 215                 | 30                   |
| Imam Jafar Sadegh      | 148                 | 28                   |
| Imam Khomeini          | 270                 | 41                   |
| Kuhdasht               | 132                 | 27                   |
| Shohada-ye Ashayer     | 347                 | 40                   |
| Shahid Chamran         | 221                 | 36                   |
| Shohada-ye Haftom Tir  | 150                 | 20                   |

Figure 16. Lorestan province hospital locations and post-disaster potential locations for medical demands.
5.5. **Sensitivity analysis.** This section aims to analyze the extent to which the fluctuation in parameters (i.e. the number of hospitals, the number of ambulances, the number of patients, and travel time) affects each of the objective function values (OFV) and then derives some managerial insights.

The average CPU time of NSGA-II and MOPSO algorithms were 639.14 and 681.57 seconds, respectively. Figures 17-20 reveal the outcomes of the mentioned investigation and the following conclusions can be drawn as follows:

- According to Fig. 17, although increasing the number of hospitals decreases the weighted sum of the latest SCT monotonously, it barely improves the second objective function, especially when the number of hospitals variation exceeds 10%. In detail, higher numbers of hospitals not only lead to lower travel times but also increase the overall hospital capacity for RC patients, which in turn enhances the first objective function more comparing to the second one. As a result, increasing the number of hospitals in the network cannot be sufficient to save more patients. However, attending capacious hospitals located in adjacent provinces is highly recommended in disaster times, especially when emergency patients outnumber overall hospital capacity in the affected area. Setting up temporary hospitals like medical camps is also an alternative step for serving lots of RC patients throughout the post-disaster phase.

![Figure 17. Alternation of OFVs according to the variation in the number of hospitals.](image)

- As Fig. 18 reveals, providing hospitals with bigger ambulance fleets results in a negligible improvement in the objective functions. It can be concluded that providing more ambulances is not an efficient way when there is a particular number of hospitals with limited capacity in the network.

- Based on Fig. 19, the objective functions are significantly sensitive to the variations in the number of patients. It should be noted that the variation slope of the second objective function is steeper in comparison to the other
one. In other words, the fewer demands are, the fewer people are in danger of becoming an RC patient or perish, whereas fewer demands cannot eliminate the key role of travel time in the performance of the first objective function. This fact necessitates steps that lead to fewer injured people, such as raising people’s awareness about safety tips that can guide them in saving themselves and others during and after a disaster.

- Fig. 20 demonstrates the undeniable influence of travel time on both of the objective functions. Furthermore, it indicates that reducing travel time can

\[ \text{OFV vs number of ambulances} \]

\[ \text{OFV vs number of patients} \]
be the best solution for decreasing the weighted sum of the latest SCT compared to the parameters variations mentioned above. Consequently, providing disaster-prone regions like Lorsetan province with faster and more sophisticated transportation modes, such as helicopters and helipad stations instead of dedicating the budgets to buying more ambulances, can lead to a notable decrease in the latest SCT and the number of casualties. Using ambulances with greater capacity can also help to save more people over a shorter period of time as it eliminates lots of repetitive travels and buys the relief group a lot of time.

It is worth mentioning that as the applied metaheuristics can provide high-quality answers in a short time, the decision makers are provided with the opportunity to evaluate the implementation of various scenarios and receive quick feedbacks to revise their approach and save lots of people before it is too late. Moreover, solving such an Np-hard problem manually may result in non-optimal or infeasible answers. Even if this is not the case, it is considerably time-consuming and puts many lives in danger.

6. Conclusion. This paper focused on developing and solving an ARP for the post-disaster phase. Patients were categorized into various groups based on their requirements and vital signs while changes in their health status were considered as well. Low computational time is a crucial necessity for such an NP-hard problem that might be solved frequently in disaster times. Therefore, two metaheuristics, including NSGA-II and MOPSO were applied to solve large-scale problems in a short response time with the aim of assisting as many patients as fast as possible. Experiments on several test problems admitted the superiority of NSGA-II over MOPSO in terms of obtaining efficient and reliable solutions. Eventually, the sensitivity analysis of some structural parameters on a real case study showed that the proposed approach can be adopted to support decisions about fleet size and

![Figure 20. Alternation of OFVs according to the variation of travel time.](image)
type as well as the number and capacities of hospitals, which in turn provides the decision-makers with some valuable managerial insights over a few minutes.

Future studies can concentrate on developing a hybrid algorithm that includes both solution methods’ strength points. They might also be extended to incorporate uncertainty in travel time, service duration, and demands or regroup the patients in each category according to the injury type.

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Appendix A. Mathematical formulation of Constraints (17) and (18).
The following formulation can be used to formulate constraints (17) and (18) in the form of mathematical inequalities:

Mathematical equivalent of constraints (17):

\[ a_i - mg \leq (1 - y_{1i}).M \quad \forall \ i \in G \]  
(27)

\[ a_i - mg \geq -(1 - y_{2i}).M \quad \forall \ i \in G \]  
(28)

\[ a_i - mg - mr \leq (1 - y_{2i}).M \quad \forall \ i \in G \]  
(29)

\[ a_i - mg - mr \geq -(1 - y_{3i}).M \quad \forall \ i \in G \]  
(30)

\[ y_{1i} + y_{2i} + y_{3i} = 1 \quad \forall \ i \in G \]  
(31)

\[ x_{gi} = y_{1i} \quad \forall \ i \in G \]  
(32)

\[ x_{ri} = y_{2i} \quad \forall \ i \in G \]  
(33)

\[ x_{di} = y_{3i} \quad \forall \ i \in G \]  
(34)

\[ y_{1i}, y_{2i}, y_{3i} \in \{0, 1\} \quad \forall \ i \in G \]  
(35)

Mathematical equivalent of constraints (18):

\[ a_i - mr \leq (1 - z_{1i}).M \quad \forall \ i \in R \]  
(36)

\[ a_i - mr \geq -(1 - z_{2i}).M \quad \forall \ i \in R \]  
(37)

\[ z_{1i} + z_{2i} = 1 \quad \forall \ i \in R \]  
(38)

\[ x_{ri} = z_{1i} \quad \forall \ i \in R \]  
(39)
\[ xd_i = z2_i \quad \forall i \in R \quad (40) \]

\[ z1_i, z2_i \in \{0, 1\} \quad \forall i \in R \quad (41) \]

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