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A cluster-based emergency vehicle routing problem in disaster with reliability

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Abstract. In the event of natural disasters, relief distribution is the most challenging problem in emergency transportation. What is important in response to disaster is victims' relief in disaster areas with the quick distribution of vital commodity. In this regard, damage to infrastructure (e.g., roads) can make trouble in designing a distribution network. Therefore, this paper considers a problem using a three-stage approach. In the first stage, pre-processing of model inputs is done through an Artificial Neural Fuzzy Inference System (ANFIS) followed by investigating the safest route for each cluster using decision-making techniques and graph theory. In the second stage, a heterogeneous multi-depot multi-mode vehicle routing problem is formulated for minimizing the transportation time and maximizing the reliability. Finally, since the routing problem is NP-hard, 2 multi-objective meta-heuristic algorithms, namely, Non-dominated Sorting Genetic Algorithm (NSGA-II) and Multi-Objective Firefly Algorithm (MOFA), are proposed to obtain the optimal solution and their performances are compared through a set of randomly generated test problems. The results show that for this routing problem, the MOFF gives better solutions than NSGA-II does, and it performs well in terms of accuracy and solution time.

1. Introduction

1.1. Motivation

The 21st century has been the century of great events of natural disasters, including the Bam (Iran) earthquake resulting in death and homelessness of many people in 2003, Indian Ocean Tsunamis because of the earthquake in 2004, Sichuan earthquake in 2008, Haiti earthquake in 2010, and the earthquake six months later in Pakistan [1]. In the latest report, the International Disaster Database1 has reported that in only two past years (i.e., 2014 and 2015) in Asia, natural disasters (e.g., extreme temperature, storm, flood, earthquake, and drought) have occurred 303 times and led to the death of 22101, injury of 119741, and homelessness of 1544234 people as well as a total economic damage of 89692926 thousand dollars [2]. Hence, the need for appropriate measures to control these horrible crises is completely understandable [3]. Since natural disasters can deprive many people of water, food, and shelter and impose the need for urgent medical help on them, completing of local capacities with the help of regional or international humanitarians is necessary [1]. Therefore, quick-responsive emergency logistics systems are efficient in providing and improving relief operations [4]. In humanitarian transport, the initial response is received 3 days after the catastrophe. Governmental and non-governmental organizations must immediately estimate the situation

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and send emergency commodity from local stores to affected points [5]. Relief operations include activities such as setting up emergency facilities, searching for survivors, providing health and medical aid, dispatching relief supplies, reassignment of victims, scheduling rescuers, and coordinating these activities between organizations [6].

The cycle of crisis management includes 4 major phases of elimination, preparedness, response, and recovery. The elimination phase includes long-term efforts for preventing disasters or reducing their effects. In the preparedness phase, before the real occurrence of a disaster, various strategic decisions and procedures (e.g., on number and location of distribution centers) are made. In the response phase, operational decisions on vehicle routing, staff and equipment, and distribution of emergency supplies to the disaster regions are made. Throughout the recovery phase, restoration of the affected areas to the prior situations is the main activity of governmental and non-governmental organizations [5].

The main purpose of transport activities in the recovery phase is to distribute essential commodities from pre-determined depots or suppliers to the affected regions and transfer wounded people to hospitals or other emergency centers [7]. After planning a transport network, relief commodities are dispatched in response phase and after the disaster. Our concentration in this paper is on the operational phase and quick distribution of emergency goods.

Vehicle Routing Problem (VRP) is one of the main and efficient problems in transportation. The vehicle passes the route between depot to demand points and returns. A certain demand is defined for each customer. Its purpose is to minimize the transport cost of all routes [8]. Relief routing models can be one-depot (i.e., relief commodities are distributed through vehicles that start and end their route on only one depot), multi-depot (i.e., vehicles start from several depots and end their routes at the same depots), or no-depot (i.e., vehicles do not return to the depot).

As mentioned, a multi-depot VRP considers situations in which there are several depots. To serve customers, each vehicle starts from one depot and follows its route, and finally returns to the same starting depot. Each customer in a given location is served by only one vehicle and the load of each vehicle does not exceed its capacity [9]. The overall demand for each route cannot exceed the vehicle capacity, and overall time of each route, consisting of travel and service, cannot exceed a pre-determined limit [10]. For organizations with more resources, models with multiple start and end points are more functional than one-depot models [1].

In a routing problem, what is significant for the flexibility of a distribution system is the heterogeneity of a transportation fleet. If heterogeneous vehicles are used in the distribution of relief goods, vehicles can be different in terms of capacity, speed, gas mileage or road, and beneficiaries that have access to them [1]. On the other hand, considering different types of distribution (i.e., road, rail, marine, and air) can make the operational system more flexible. However, this assumption has been addressed in a few studies. In multi-mode transportation, the possibility of taking advantage of more than one vehicle type can speed up the distribution operation and make it possible in the case of road crash or bad weather conditions.

An efficient approach for distribution of relief goods, which is rarely used in this context, is to cluster the affected areas. In this way, areas with similar needs are identified and prioritized. For clustering data, it is possible to use neural network methods, such as Artificial Neural Fuzzy Inference System (ANFIS) technique. The necessity of considering distribution priorities and safe routes is an issue somewhat neglected. What is first considered in humanitarian assistance is whether routes have the ability to rapidly deliver humanitarian goods or not [11]. Shipping relief goods to the prioritized affected areas plays an important role in saving survivals. This can be achieved by applying various criteria including route reliability for clustering affected areas. Considering the reliability can make the model more efficient. In other words, some trouble in the vehicles' route may be an obstacle to them reaching their destinations. Therefore, an objective function can be defined as maximizing travel reliability [11].

Saadatseresht et al. [12] formulated an affected population evacuation planning model in an earthquake disaster and solved it by multi-objective evolutionary optimization algorithm, NSGA-II. The related results showed the validity of the model. Afshar Najafi and Razmi-Farooji [13] suggested a vehicle routing model with time windows, heterogeneous fleet, and multiple depots. They suggested two well-known methods of NSGA-II and MOSA for solving their model. Simic et al. [14] presented a routing model with heterogeneous fleet of vehicles in logistics distribution. In fact, this study presented the hybrid of genetic and firefly algorithms, in which the genetic algorithm was used in the first step of the optimization process and capacity zones definition, and the firefly algorithm was used in the second step in this model. The reader may refer to Zheng et al. [15] for further information on all classifications of evolutionary algorithms used in disaster relief operations.

This paper tries to model a relief distribution network after the event of a catastrophe in a response stage that uses heterogeneous vehicles in multi-depot and multi-mode circumstances. The ANFIS technique is also applied for clustering affected areas before distributing goods. Furthermore, to accelerate relief distribution operations, demand points are prioritized according to the factors affecting the network reliability using a graph theory-multi attribute-permanent matrix (GT-MP-DM). Since most meta-heuristic algorithms are oriented to NSGA-II as a powerful tool, most studies in the routing field have used this algorithm for multi-objective optimization problems. On the other hand, the multi-objective firefly algorithm has good performance in vehicle routing problems; therefore, in this paper, we applied these algorithms (NSGA-II and multi-objective firefly algorithms).

1.2. Related work

Among the issues increasingly addressed in studies is a relief routing problem in humanitarian logistics. Knott [16,17] was a pioneer in the crisis relief operations design. He developed two models in 1987 and 1988, in which relief goods in one- or multi-commodity flow were shipped from one distribution center (i.e., depot) to several camps. Those studies considered equity in distribution and were aimed to minimize unfulfilled demands.

Following that, several studies were conducted in the context of relief routes. One group of these studies, such as Barbasuglu [18,19] and Haghani and OH [20,21], concentrated on a routing problem and distribution of emergency goods. These studies were to minimize time and cost of transportation and assumed that several relief goods from several depot were shipped by heterogeneous vehicles to the affected areas. Yi and Ozdemir [22] and Ozdamar et al. [23] considered heterogeneity of vehicles for distributing several types of relief goods with the purpose of decreasing unmet demand of affected areas. A multi-mode transportation fleet (i.e., ground, marine, and air) made the model more efficient and flexible in the real world. Therefore, Barbasoglu [19], Rennemo et al. [24], Hu [25], Najafi et al. [26], Adivar and Mert [27], and Ozdamar [28] followed this issue in separate studies.

Among the most recent studies in relief routing, Goli and Alinaghian [29] addressed a VRP of relief goods distribution from several depots using a covering tour problem. In a significant study by Talarico et al. [30], an emergency ambulance routing problem was modeled in such a way that patients were grouped and prioritized before evacuation.

On the other hand, accounting for the probability of failure and reliability is a necessity in relief distribution operations, which has rarely been considered. Vitoriano et al. [31] considered this necessity and presented a goal programming model with objectives such as reliability and possibility of ransack attribute, in which heterogeneous vehicles delivered one relief good from multiple depots to affected areas. In recent years, Hemedi et al. [32] based their model on the premise that there was the possibility of failure by minimizing the reliability cost of the model. This model was developed for a relief distribution problem with multiple depots. Najafi et al. [26] considered relief distribution and evacuation of wounded people. This probabilistic model was developed assuming multiple commodities, periods, and modes in the response phase.

Among the most recent studies, Nasiri and Shishe-Gar [11] considered relief routing in which prioritization and reliability were considered from a graph theory and permanent matrix viewpoint, and finally presented a model aimed to maximize reliability and, at the same time, reduce the total cost of the relief process. In this network, trucks with different capacities delivered one relief good to affected areas through the fastest routes possible.

Few previous studies have addressed clustering in a VRP, but only in the case of non-disaster context. The study by Dondo and Gerda [33] was one of them. Using a heuristic/algorithmic approach, they clustered demand points and dedicated them to vehicles in a multi-depot heterogeneous VRP based on time windows. He et al. [34] considered clustering of demand points for commodity distribution in a large-scale VRP and partitioned the city into several regions by use of balanced K-means clustering.

A neuro-fuzzy system in relief routing problems has been used in some studies. For instance, Dehnavi et al. [35] divided the affected areas by implementing a hybrid model of ANFIS and a statistical index in a geographical information system; their model was applicable in the primary planning earthquake. Zheng et al. [36] addressed a logistic model for relief goods distribution and classified the affected people by considering a neuro-fuzzy system. They solved the model by a Differential Biography-Based Optimization (DBBO) algorithm. Zheng et al. [37] suggested the emergency evacuation model and used a Multi-Objective Partial Swarm Optimization (MOPSO) algorithm for the classification of affected people in fire evacuation operations. Rath and Gutjahr [38] presented a location-routing model for the relief items distribution and solved the model by NSGA-II and a meta-heuristic algorithm.

Through reviewing the related literature and investigating the existing gap in studies, we propose a relief routing model increasing the reliability and decreasing the transport time. In this model, clustering of affected points is first done. For clustering, the use of fuzzy C-means in an ANFIS network is considered. Next, affected areas of each cluster are prioritized. Relief goods from different depots are delivered by heterogeneous vehicles to the prioritized affected areas.

The other sections in this paper are organized as follow. A summary of research steps is schematically shown in Section 2, followed by the explanation of the 3 steps for conducting the research. Section 3 presents the computational results. Finally, results and suggestions for future research are given in Section 4.

2. Research method

In this study, clustering of the affected points and investigation of reliability are carried out in 3 stages. The steps are shown in Figure 1, which will be discussed in details.

2.1. Clustering (Stage 1)

2.1.1. Problem description

After the occurrence of an earthquake in a region, humanitarian organizations make substantial efforts to distribute emergency commodity to the disaster regions. To distribute relief goods to the affected area, routing operations are performed. To accelerate distribution of relief goods, the affected areas are clustered according to the criteria, such as crisis severity, distance of points from the depots, road risk, the slope and width of the road leading to the affected point, weather conditions at the time of crisis, and population density. The first cluster includes the affected points whose leading routes and infrastructure of the regions are usable and there is the possibility of ground relief. The second cluster includes the affected points in which, because of damage and disruption in vehicle routes, only air relief operations are possible. Therefore, we encounter a routing problem that is multi-depot and relief operations are done in multiple modes (ground, and air), the applied vehicles in the response phase are heterogeneous (i.e., different in velocity and capacity), and the relief commodity is one package (one-commodity) consisting of the first aid kit, can, mineral water, blanket, and tent (Figure 2).

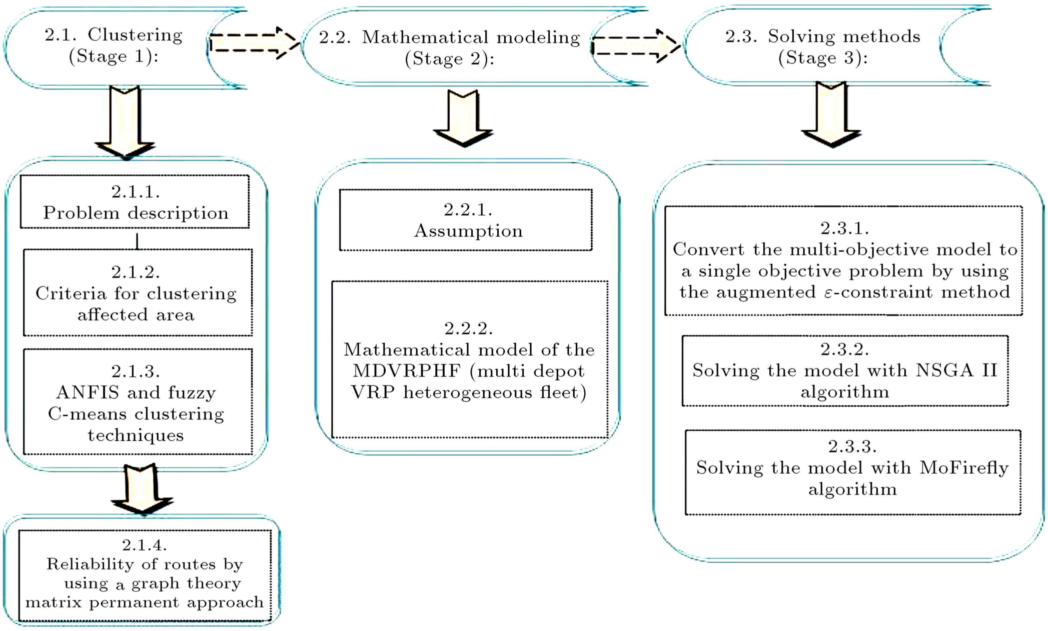

Figure 1. Schematics of the research method.

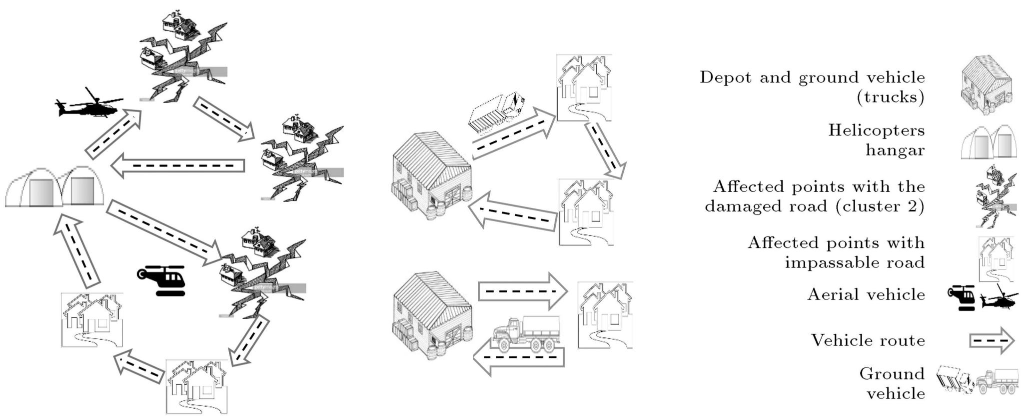

Figure 2. Relief distribution network and clustered affected points.

2.1.2. Criteria for clustering the affected areas

Since rapid response to the affected areas is critical in times of crisis, clustering of the affected points is proposed in this paper to accelerate the distribution procedure. Clustering of the affected points is carried out by applying an ANFIS network according to a fuzzy C-means algorithm. According to the measures like road type, geographical properties (for road routes), severity of the crisis, regional texture, and population of affected region (for other points that have damage roads), these points are grouped into two clusters; cluster 1: points with healthy routes, and cluster 2: points with damaged routes. According to the two clusters, the relief is also divided into ground and aerial types. Relief to the points in cluster 1 is carried out in both ground and aerial modes; but, for points of cluster 2, relief operations are done only through air.

2.1.3. ANFIS and fuzzy C-means clustering techniques

We need a system that can be trained without specialized knowledge. Hence, we apply ANFIS. It is a fuzzy model performed on adaptive systems for the ease of learning [39]. ANFIS structure includes 5 layers with forward and backward motions to update the consequent and the primary parameters through the Least Square Error (LSE) estimate and the Gradient Descent (G.D) method, respectively [40].

The ANFIS looks for updates and error reduction in output by the use of forward and backward passes. A forward pass obtains the output. If there is a difference (or error) between the optimal solution and the output value, updating is performed by using a least square error. Backward pass updates the output by the use of a gradient method. The fuzzy inference system is a first-degree Sugeno fuzzy model with first order output membership function. There are several techniques for clustering data, including fuzzy C-means method. The first version of this algorithm, developed by Doda and Hart [41], is exact clustering, because some of the data are related to several clusters and it is not possible to place them in one cluster. Therefore, Dunn [42] developed the fuzzy version of this algorithm. The fuzzy C-means is a clustering technique in which each point belongs to a group with a certain degree (that is identified according to the membership score) and it aims to improve the efficiency of the previous clustering methods [43].

To illustrate the steps of the ANFIS, clustering is performed in 2 phases as follows. In phase 1, data are pre-processed and clustered in a trial and error process using a fuzzy C-means method. In this phase, the structure of the fuzzy inference system is formed based on a fuzzy Sugeno model. In phase 2, having prepared the data, creation and training of ANFIS will be performed. Through the training procedure, membership function parameters are changed. Change and modification are performed through measurement of the error. Because the main rule of training is based on the descent gradient method, the features of which are slowness and being trapped in local minimum, the method selected for optimal training of ANFIS parameters is a hybrid of back propagation and LSE.

The back propagation method identifies nonlinear and non-desired parameters and, eventually, ideal outputs are determined by the least square method. From all the data, 80% of input and output data pairs are randomly chosen for the training of the ANFIS and the remaining 20% are applied for the test of the ANFIS [44].

The results will be assessed by error values and correlation between the ANFIS and available test data as shown in Table 1. It can be said in summary that in this phase, the ANFIS model is created and trained according to the clustered data. Tuning of parameters is done in this phase to train the network and, then, the fitness of the network is assessed by using the confusion matrix and accuracy percent.

2.1.4. Reliability of routes by using a graph theoretical-matrix permanent approach

Nowadays, road networks with high reliability are needed to ensure drivers' safety in fluctuations of traffic flow and avoidance of unforeseen delays caused by network disruptions [45]. In this study, reliability is defined based on "graph theoretical-matrix permanent-decision making" as concepts of multi-criteria decision making, which results in determination of the best route with maximum reliability.

The GT-MP-DM approach includes the diagraph, the matrix, and the permanent function display. The diagraph is the visual display of the factors and their interdependence. The permanent function helps to define reliability index [46]. By these explanations, the GTA converts qualitative factors to quantitative values [47]. In this study, the diagraph is the visual display of factors affecting reliability. To become familiar with the GTA-permanent matrix, we illustrate it in the following 3 steps:

Step 1: Specification of the criteria, sub-criteria, and alternatives required for the current multi-criteria theoretical problem. In this step, all affecting factors on the decision are determined, which can be obtained from related criteria in the literature or selected by the experts according to a diagraph representation of factors and their interdependencies [48]. According to these definitions, in this study, crisis severity, the type of regional context (urban/rural), weather conditions, population of the affected area, type of road, and mountainous rate can be stated as affecting criteria for the selection of the reliable route. To represent a graph in this step, we have to know

Table 1. Numerical examples for clustering of affected points with the ANFIS method.

Affected points	Road slope	Weather conditions in disaster situations	Intensity of disaster	Population density	Road risk	Distance of vehicle from depot1 (truck) km	Distance of vehicle from depot2 (truck) km	Distance from airport (Helicopter) km	Width road (m)	Cluster no.
1	Low	Normal	Very great	2739	Low	8	5	0	12	1
2	Low	Normal	Very great	3100	Low	12	8	11	8	1
3	Low	Normal	Great	2050	Low	10	5	10	8	1
4	Low	Good	Great	450	Low	8	5	1	12	1
5	Low	Good	Very great	850	Low	9	5	3	12	1
6	Low	Good	Great	1416	Low	3	10	13	12	1
7	Medium	Good	Medium	1200	Medium	5	13	16	8	1
8	Medium	Normal	Medium	1020	Medium	6	14	17	8	1
9	High	Bad	Medium	1201	Medium	7	14	19	8	2
10	High	Bad	Great	500	Medium	8	15	20	8	2
11	High	Normal	Very great	900	Medium	67	70	75	12	2
12	High	Bad	Very great	1316	Medium	65	72	77	12	2
13	High	Bad	Very great	800	Medium	68	71	77	8	2
14	Medium	Normal	Great	500	Medium	8	13	18	8	2
15	Medium	Good	Great	351	Medium	9	15	20	8	1
16	Medium	Good	Great	450	Medium	9	11	16	8	1
17	Medium	Normal	Great	500	Medium	18	16	13	12	2
18	Low	Normal	Great	7703	Medium	25	4	15	8	1
19	High	Bad	Very great	2584	High	75	70	65	8	2
20	High	Bad	Very great	204	High	87	82	78	8	2

that this graph includes all of the nodes, $N = \{n_i\}$, where $i = 1, 2, ..., M$. Each node, n_i, represents the ith route reliability criterion and each edge shows the relative importance of the criterion. The number of nodes, M, is equal to the number of selection criteria. If node i is more important than node j, a directed edge is drawn from i to j (e.g., e_{ij}) and vice versa [49]. To better understand this approach, the graph along with criteria, sub criteria, and interaction between them, based on a graph theoretical-matrix permanent-decision making approach, is depicted in Figure 3 (criteria are represented with C_i) [50].

Step 2: Definition of the relative importance of criteria and the scores of alternatives at each criterion. If qualitative target values are available, alternative scores can be obtained by standard tests. Otherwise, a ranking scale from 0 to 10 can be used as shown in Table 2 [51]. Normalized criteria's quantitative values are specified for any values. The resulting normalized values are divided by v_i on v_j (v_i is the amount of the criteria for the ith alternative and v_j is the amount of the criterion of the j-th alternative). If the criteria value is higher utility than the normalize values calculated by the resulting divide v_j on v_i [50]. At beneficial criteria, the lower and upper limit of the alternative C_i assigned 0 and 1, respectively, and for the other in the inter-values definition in Eq. (1). It means that 0 is assigned to the highest value (C_{iu}) and 1 is assigned to the lowest value (C_{il}). The other intermediate values can be determined by using Eq. (2) [51]:

Table 2. Quantitative scores of alternatives.

Qualitative measure	Crisp score
Exceptionally low	0
Extremely low	1
Very low	2
Low	3
Below average	4
Average	5
Above average	6
High	7
Very high	8
Extremely high	9
Exceptionally high	10

$$C_i = (C_{ii} - C_{il})/(C_{iu} - C_{il}), \tag{1}$$

$$C_i = (C_{iu} - C_{ii})/(C_{iu} - C_{il}). \tag{2}$$

Then, the criteria rating matrix (ψ) is calculated by using Eq. (3). According to the 6 scales of Ta-

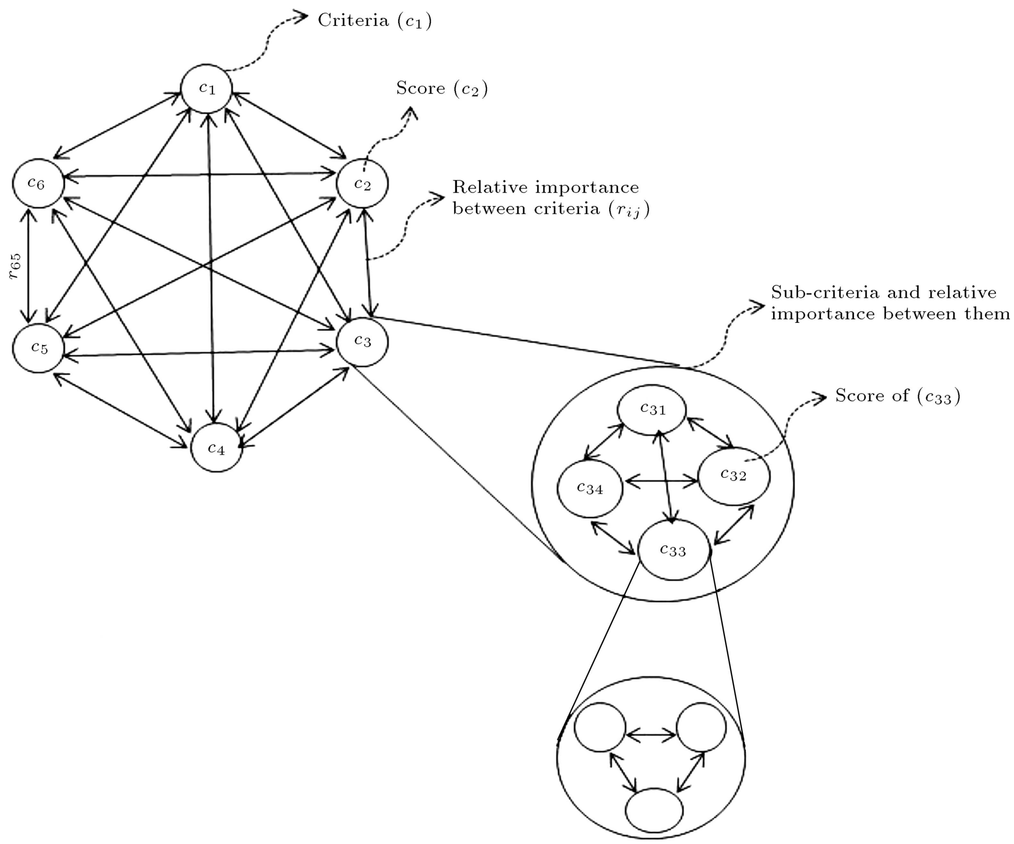

Figure 3. Criteria and sub-criteria framework for GT-MP-DM.

Table 3. Relative importance of criteria.

Class definition	r_{ij}	$r_{ji} = 1 - r_{ij}$
Two criteria equally important	0.5	0.5
One criterion slightly more important than the other	0.6	0.4
One criterion more important than the other	0.7	0.3
One criterion much more important than the other	0.8	0.2
One criterion significantly more important than the other	0.9	0.1
One criterion important, others not important	1.0	0.0

ble 3, the relative importance (symmetric or non-symmetric) of a criterion can be a value between 0 and 1. This value can be obtained by the decision maker as well. As it can be seen from Table 3, $r_{ji} = 1 - r_{ij}$ and there is no requirement on this relationship to hold for. It may hold or they can be evaluated independently. Thus, the relative importance (interaction) matrix, β, can be symmetrical or non-symmetrical [51]:

$$[\psi] = \begin{bmatrix} C_{11} & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & C_{nn} \end{bmatrix}, \tag{3}$$

$$[\beta] = \begin{bmatrix} 0 & \cdots & r_{1n} \\ \vdots & \ddots & \vdots \\ r_{n1} & \cdots & 0 \end{bmatrix}. \tag{4}$$

Step 3: Obtaining the alternative by evaluation matrix. In this step, we obtain a permanent value of this matrix for any alternative. Coinciding the development of the determinant, Muir [48] defined a certain subclass of symmetric functions (permanent). The only difference between determinants and permanents is the minus sign, which appears instead of a plus sign in calculating these quantities [48]. If we use permanent, then, we do not have any negative sign (unlike determinant); as a result, no information would be lost [49]. The permanent matrix, ξ, is obtained through the rates of alternatives by Eq. (5). The values must be sorted in descending order and the highest value is the best alternative (the most reliable route) [50]:

$$per(\xi) = \Pi_{i=1}^{N} c_i + \sum_{i,j,\ldots,N} (r_{ij}.r_{ji}).c_k.c_l \ldots c_N + \sum_{i,j,\ldots,N} (r_{ij}.r_{jk}.r_{ki} + r_{ik}.r_{kj}.r_{ji}) .c_l.c_n \ldots c_N + \left\{ \left\{ \sum_{i,j,\ldots,N} (r_{ij}.r_{ji})(r_{kl}.r_{lk}) .c_n.c_m \ldots c_N + \sum_{i,j,\ldots,N} (r_{ij}.r_{jk}.r_{kl}.r_{li} + r_{il}.r_{lk}.r_{kj}.r_{ji}).c_n.c_m \ldots c_N \right\} \right\} + \left[\sum_{i,j,\ldots,N} (r_{ij}.r_{ji})(r_{kl}.r_{ln}.r_{nk}).c_m.c_o \ldots c_N + \sum_{i,j,\ldots,N} (r_{ij}.r_{jk}.r_{kl}.r_{ln}.r_{ni} + r_{in}.r_{nl}.r_{lk}.r_{kj}.r_{ji}).c_m.c_o \ldots c_N \right] + \ldots \quad (5)$$

In the following, the steps of applying GT-MP-DM to a relief routing problem to prioritize affected points of clusters 1 and 2 are described. It is worth mentioning that prioritization criteria for the affected points of cluster 1 are related to the route reliability, and prioritization of affected points of cluster 2 is based on the other criteria that affect the acceleration of relief distribution operations, as mentioned before. By using an example, this procedure is explained below.

In the first step, by a survey of earlier research on a relief routing problem and by several databases (including the International Disaster Database, Earthquake Database of Australia, Canadian Disaster Database, etc.), we extract the criteria that influence the route reliability. According to this disquisition, the type of road (e.g., autobahn, arterial, highway, or lane), mountainous rate of the road, geographical characteristics (prioritization criteria of cluster 1), crisis severity, regional texture (urban or rural), weather condition, and distance of depot to affected areas (prioritization criteria of cluster 2) affect the reliability of routes. Next, in the second step, we obtain matrix β, the elements of which identify the relative importance of criteria, and criteria rating matrix ψ, for each cluster and each alternative. Following that, in the third step, the permanent matrix is calculated. According to a random example, the results are as follows (affected points 1 and 2 falling in cluster 1):

$$[\psi_{1-2}] = \begin{bmatrix} 0.4 & 0 & 0 & 0 \\ 0 & 0.5 & 0 & 0 \\ 0 & 0 & 0.2 & 0 \\ 0 & 0 & 0 & 0.4 \end{bmatrix},$$

$$[\beta] = \begin{bmatrix} 0 & 0.2 & 0.4 & 0.1 \\ 0.8 & 0 & 1 & 0.5 \\ 0.6 & 0 & 0 & 0.3 \\ 0.9 & 0.5 & 0.7 & 0 \end{bmatrix},$$

$$[\zeta_{1-2}] = \begin{bmatrix} 0.4 & 0.5 & 0.8 & 0.4 \\ 0.5 & 0.5 & 0.9 & 0.5 \\ 0.2 & 0.1 & 0.2 & 0.2 \\ 0.6 & 0.5 & 0.8 & 0.4 \end{bmatrix},$$

$$Per(\zeta_{1-2}) = 0.7.$$

2.2. Mathematical model (Stage 2)

2.2.1. Assumptions

The main assumptions of the presented model are as follow:

- The number of relief vehicles is limited and different types of them are applied to serve affected areas. Consequently, transportation fleet is heterogeneous in velocity and capacity of vehicles;
- Start point of all vehicles is already known. It identifies which vehicle belongs to which depot;
- In the case of a large-scale incident, use of all the vehicles will be required;
- Each affected point is served by only and only one vehicle;
- The capacity of the vehicle is more than demand so that there is no disruption in service operations;
- The location of relief goods distribution and depots is the same;
- The inventory of depots is sufficient to respond to the affected areas;
- Distribution operations take place for one package of reliefs that contains the first aid kit, can, mineral water, blanket, and tent;
- The location of any affected area as well as its distance from depots is known;
- The amount of demand at each affected point is known;
- Each vehicle returns to its starting point after the end of operations;

- Relief distribution operations are performed through multiple depots and depots of relief goods are the holding station of vehicles as well, in which some goods are in a holding station of ground vehicles (i.e., trucks) and the other goods are in the helicopters' hangar (i.e., holding station of air vehicles) located at the airport;
- The affected points fall in two clusters, and all points of each cluster are prioritized by affecting factors on reliability.

2.2.2. *Mathematical model of the MDVRPHF (Multi-Depot VRP heterogeneous fleet)*

The following parameters and variables are described, followed by the mathematical model.

Notations and sets

v'	Set of ground vehicles-set of trucks
vv	Set of aerial vehicles-set of helicopters
e	Set of affected points with passable road
ee	Set of affected points with damaged road
d	Set of ground vehicle depots
dd	Set of helicopter hangars
N	Number of all nodes
$n_{v'}$	Number of trucks
n_{vv}	Number of helicopters
n_e	Number of points with passable road
n_{ee}	Number of points with damaged road
n_d	Number of trunk depots
n_{dd}	Number of helicopters' hangars
V	Set of vehicles

Parameters

Cap_v	Capacity of vehicle type v
Dem_i	Demand of node i (affected point)
t_{vij}	Travel time of vehicle from node i to node j
r_{ij}	Permanent value of node i to node j according to reliability index
U_{vi}	Auxiliary and sequential variables that show the number of nodes being visited by vehicle v in sub-tour elimination constraints

Decision variable

$$x_{vij} = \begin{cases} 1 & \text{if vehicle } v \text{ travels from node } j \\ 0 & \text{otherwise} \end{cases}$$

Mathematical model

Now, our proposed model can be mathematically formulated by:

$$\text{Min}(\text{Max} \sum_{i\in I} \sum_{j\in J} \sum_{v\in V} t_{vij} x_{vij}), \tag{6}$$

$$\text{Min} \left(\sum_{i\in I} \sum_{j\in J} \sum_{v\in V} r_{ij} x_{vij} \right), \tag{7}$$

s.t.

$$\sum_{i\in n_e \cup f(v,i)} x_{vij} = \sum_{i\in n_e \cup f(v,i)} x_{vji} \quad \forall j \in n_e, v \in n_{v'}, \tag{8}$$

$$\sum_{i\in n_e \cup n_{ee} \cup f(v,i)} x_{vij} = \sum_{i\in n_e \cup n_{ee} \cup f(v,i)} x_{vji}$$

$$\forall\, j \in n_e \cup n_{ee}, v \in n_{dd}, \tag{9}$$

$$\sum_{i\in f(v,i)} \sum_{j\in n_e} x_{vij} = 1 \quad \forall\, v \in n_{v'}, \forall f(v,i), \tag{10}$$

$$\sum_{i\in f(v,i)} \sum_{j\in n_e \cup n_{ee}} x_{vij} = 1 \quad \forall\, v \in n_{dd}, \tag{11}$$

$$\sum_{i\in n_e} \sum_{j\in f(v,i)} x_{vij} = 1 \quad \forall\, v \in n_{v'}, \tag{12}$$

$$\sum_{i\in n_e \cup n_{ee}} \sum_{J\in f(v,i)} x_{vij} = 1 \qquad \forall v \in n_{dd}, \tag{13}$$

$$\sum_{V\in n_{v'}} \sum_{j\in n_e} x_{vij} + \sum_{v\in n_{vv}} \sum_{j\in n_e \cup n_{ee} \cup f(v,j)} x_{vij} = 1$$

$$\forall i \in n_e, \tag{14}$$

$$\sum_{v\in n_{vv}} \sum_{j\in n_e \cup n_{ee} \cup f(v,j)} x_{vij} = 1 \quad \forall i \in n_{ee}, \tag{15}$$

$$\sum_{j\in n_e \cup f(v,j)} \sum_{i\in n_e} x_{vji} {}^* \, \text{dem}_i \quad \leq \quad \text{Cap}_v$$

$$\forall\, v \in n_d \cup n_{dd}, \tag{16}$$

$$\sum_{j\in n_e \cup n_{ee}} \sum_{i\in n_e \cup n_{ee}} x_{vji}{}^* \text{dem}_i \quad \leq \quad \text{Cap}_v$$

$$\forall\, v \in n_{vv}, \tag{17}$$

$$U_{vi} - U_{vj} + n_e{}^* X_{vij} \leq \; n_e - 1$$

$$\forall\, v \in n_{v'}, \forall i \in n, \forall i \in n_e, \tag{18}$$

$$U_{vi} - U_{vj} + n_{ee}{}^* X_{vij} \leq \; n_{ee} - 1$$

$$\forall v \in n_{v'v}, \forall i \in n_e \cup n_{ee}, \forall i \in n_e \cup n_{ee}, \tag{19}$$

$$U_{vi} \leq n_e \quad \forall v \in n_{v'}, \forall i \in n_e, \tag{20}$$

$$U_{vf(v,i)} = 0 \qquad \forall v \in n_{v'}, \forall i \in n_e, \tag{21}$$

$$U_{vi} \leq n_e \cup n_{ee} \qquad \forall v \in n_{vv},\ \forall i \in n_e \cup n_{ee}, \tag{22}$$

$$U_{v.f(v,i)} = 0 \qquad \forall v \in n_{vv}, \forall i \in n_e \cup n_{ee}, \tag{23}$$

$$U_{vi} = \{0, 1, 2, ...\}, \tag{24}$$

$$x_{vij} \in \{0, 1\} \qquad \forall v, i, j. \tag{25}$$

The objective function (6) minimizes the maximum transportation time of vehicle v between node i and node j. The objective function (7) maximizes the reliability of routes through maximizing sum of the permanents of each route. Constraint (8) guarantees the balance of flow for the affected points with healthy road for ground vehicles. That is, each truck after entering the node and serving the point leaves the node. Constraint (9) guarantees the balance of flow for healthy and not-healthy points and for helicopters. In other words, the helicopters leave the node after the entrance to it. Constraint (10) indicates that the start point of any truck is known to be from what depot, while Constraint (11) is the constraint on the start point of helicopters. Constraints (12) and (13) guarantee that any vehicles (i.e., truck and helicopter) after serving any nodes must come back to the start point and the route is closed. Constraint (14) ensures that each vehicle (i.e., helicopter or truck) only serves one node (a point with healthy leading road) and consequently, Constraint (15) identifies that each vehicle (helicopter) serves only one unhealthy node (affected point with damaged leading road). Constraints (16) and (17) are the capacity limitations of trucks and helicopters. The part considered as sub-tour constraint is represented in Constraints (18) to (23), among which Constraints (18) and (19) are the sub-tour elimination constraints for trucks and helicopters, Constraints (20) and (21) are the sub-tour elimination constraints for axillary variables, U_{vi} and $U_{vf(v,i)}$, for trucks, and Constraints (22) and (23) are the sub-tour elimination constraints for axillary variables U_{vi} and $U_{vf(v,i)}$ for helicopters. Finally, Constraint (24) refers to the sequence of U_{iv} and Constraint (25) refers to binary variables, x_{vij}.

2.3. Solution methods

2.3.1. Augmented ε-constraint method

Now, through the augmented ε-constraint technique, the multi-objective function is converted to a single-objective function. Consider the following multi-objective function:

$$\text{Min}\left(f_1(x), f_2(x), ..., f_p(x)\right),$$
$$\text{S.t.}$$
$$x \in s, \tag{26}$$

where x is the decision variables vector, $f_1(x), ..., f_p(x)$ are the p objective functions, and s is the feasible area. In this method, we optimize one of the objective functions and put the other objective functions in constraints (Eq. (27)):

$$\text{Min} f_1(x)$$
$$\text{S.t.}$$
$$x \in X$$
$$f_2(x) \leq \varepsilon_2$$
$$f_3(x) \leq \varepsilon_3$$
$$\vdots$$
$$f_p(x) \leq \varepsilon_p. \tag{27}$$

Through setting the ε parameters, the efficient solution is obtained. Three issues that need attention in the implementation are: (1) computation of the domain of the objective functions about efficient set; (2) assurance of the performance of the obtained solution; and (3) consideration of increased time for multi-objective problems [52].

In this paper, an augmented ε-constraint method is presented to consider the above-mentioned issues. In this study, we apply the Mavrotas [53] method to use the multi-objective functions problem [53]. The steps of augmented ε-constraint method are as follows:

1. The main objective function is selected randomly among the objective function;
2. Considering one of the objective functions each time, the problem is solved and the optimal value of each objective function is obtained;
3. Using the Lexicographic method, the best and the worst amounts of each objective function are obtained such that the best value of the first objective function is equal to its optimum in optimization of a problem by considering objective functions individually. Next, by optimizing the second objective function, under the constraint that the first objective function remains at its optimal value, the worst value of the second objective function is specified. This procedure is continued until the

optimization of all objective functions (Eqs. (28) and (29)):

$$[f_i^{\max},\ f_i^{\min}], \tag{28}$$

$$r_i = f_i^{\max} - f_i^{\min}. \tag{29}$$

4. The region between two optimum solutions of the subsidiary objective function is divided into a pre-specified number of regions (q_i) and a table of ε values, which is obtained by:

$$\varepsilon_i^k = f_i^{\max} - \frac{r_i}{q_i} * k \qquad k = 0, 1, ..., q_i. \tag{30}$$

5. The problem with the main objective function is solved by considering one of the ε values each time and, accordingly, the region of each objective function is obtained. Mavrotas [53] showed that the obtained solutions of ε-constraint method had little efficiency. To overcome this deficiency, he proposed changing the constraints of the objective function to equality constraints by using proper slack and surplus variables. These variables, as the second sentence (with lower preference), lead the program towards the generation of efficient solutions. The new problem is defined as follows.
6. Finally, the obtained Pareto solutions are reported [52]:

$$\begin{aligned}
&\text{Min}\left\{f_1(x) - \delta * (s_2 + s_3 + ... + s_p)\right\},\\
&f_2(x) = \varepsilon_2 - s_2,\\
&f_3(x) = \varepsilon_3 - s_3,\\
&\vdots\\
&f_p(x) = \varepsilon_p - s_p,\\
&x \in X,\ s_i \in R^+.
\end{aligned} \tag{31}$$

Description of a VRP is simple; however, solving it is difficult. The VRP usually takes exponential time to obtain the optimal solution. In the following sections, two multi-objective meta-heuristics, namely, NSGA-II and Mo firefly, are explained.

2.3.2. NSGA-II algorithm

Deb et al. [54] presented a Non-dominated Sorted Genetic Algorithm (NSGA) for solving multi-objective optimization problems. The main features of this algorithm are as follows:

1. Defining density as a feature space for alternative ways, such as fitness sharing;
2. Using binary tournament selection operator;
3. Storing and archiving non-dominated solutions gain in the prior steps of the algorithm (i.e., elitism).

There are optimization algorithms that, instead of one distinct solution, identify a set of solutions, named Pareto front, among which none has absolute dominance over the others. The Meta heuristic NSGA-II algorithm is converted to a multi-objective algorithm by adding two required operators that, instead of finding the best solution, give a set of best solutions known as Pareto front. These two operators are: (1) The operator that assigns a population member as a rank according to non-dominance sorting; and (2) The operator that maintains solution diversity across the solutions with equal ranks [54].

To generate solutions with suitable quality and order, the NSGA-II performs the following steps [55]:

1. **Initial population:** In the NSGA-II, a population size is considered (*npop*). First, a random population of size *npop*, named *pop*, is generated and the value of each function is computed for every member of the initial population;
2. **Non-dominance sorting:** After computing the objective functions, non-dominance sorting is applied to the population using the non-dominance concept. Actually, in this way, the population members that are in different levels of non-domination are categorized into several fronts. The population members that are not dominated at all form a set of non-dominated solutions (i.e., Pareto front). The fitness that is equal to the non-dominance level (level number) is attributed to any solution of the population. Hence, fitness minimization is desired;
3. **Sorting by crowding distance:** To sort the solutions that have the same rank and are in one non-dominance level, a secondary measure, namely, crowding distance, is used. This crowding distance for solution i is an estimation of a rectangle's diameter whose vertices are the closest neighbor solutions to it in its front;
4. **Crossover operator:** At each iteration, the crossover operator is applied to a part of the current population and the new npop*pcrossover solution is generated. The value of each objective function is obtained for each member of the new population to select parent solutions utilized for binary tournament selection. The steps of any iteration of the NSGA-II are schematically shown in Figure 4. The algorithm is finished when a user-specified number of iterations is exceeded;
5. **Child evaluation and sorting the population:** We will select the N first members from the total population.

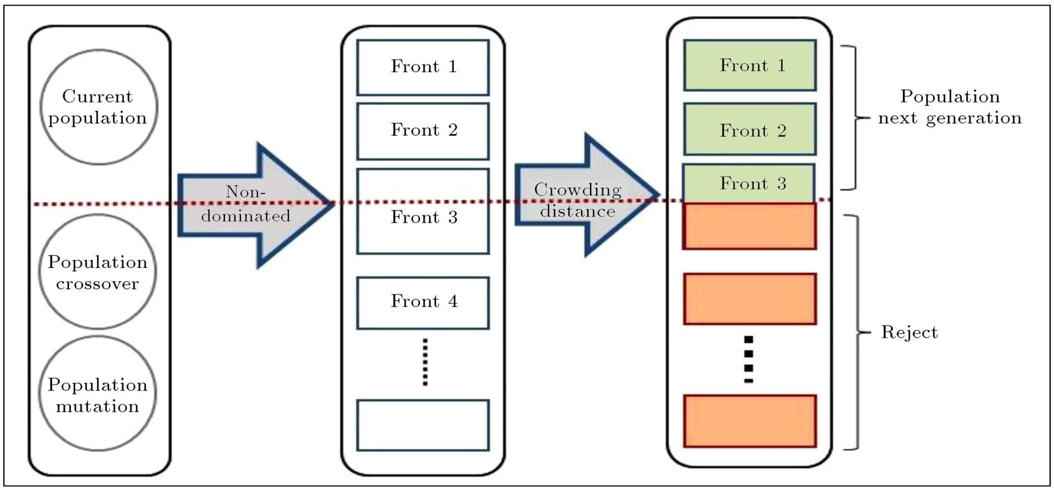

Figure 4. Steps conducted in each iteration of the NSGA-II.

```
Begin
    Step 1: Initialization. Set the generation counter G = 1: Initialize the population of n
            Firefly P randomly and each firefly corresponding to a potential solution to the
            given problem:
            Define light absorption coefficiently:
            Set controlling the step size α and the initial attractiveness β0 at r = 0.

    Step 3: Evaluate the light intensity I for each firefly in P determined by f(x)
            while the termination criteria is not satisfied or G <Max generation do
            For i = 1: n (all n fireflies)
               For j = 1: n (n fireflies) do
                  If (Ij < Ii)
                           Move firefly i toward j;
                          end if
                                Vary attractiveness with distance r via exp (−γ^(r^2));
                                Evaluate new solutions and update light intensity;
                             End for j
                           End for i
        G = G + 1;
    Step 4: end while
    Step 5: post-processing the results and visualization;
End
```

Figure 5. Pseudo-code of the firefly algorithm.

If the termination condition is reached, we have the output solution and the end. Otherwise, we come back to the steps 4, 5, and 6 [56].

2.3.3. MO firefly algorithm

The firefly algorithm is a new swarm intelligence optimization inspired by the characteristics and flash partner of fireflies [57]. The following mainframe and firefly algorithm are described.

Mainframe of firefly algorithm

One of the active researchers in the field of nature-inspired algorithms for optimization problems was Yang and Gandhi [51] who developed the first version of the Firefly algorithm (FA). This algorithm was inspired by small luminous insects called the fireflies [58]. There are several motivations behind firefly luminescence [59], e.g. attracting a mating partner and conservation against hunters. The algorithm is controlled by 3 laws [58]:

1. All fireflies are unisex. That is, the fireflies are not attracted to each other according to a particular gender [59];
2. The reason for firefly's high attractiveness is its brightness value. The more the value, the higher the attractiveness is. By increasing the distance between two fireflies, lighting and attractiveness are reduced;
3. There is clear relation between the brightness of firefly and the objective function value. More lighting results in more objective function and leads to a better solution [58]. In fact, the objective function of this algorithm is fitness function of the genetic algorithm [14]. Figure 5 represents a firefly

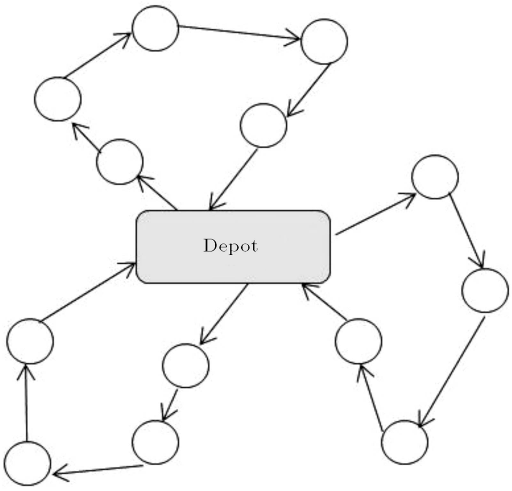

Figure 6. Vehicle routing problem.

and the pseudo-code of firefly algorithm that shows an initialization, a moving factor, and an objective function [60].

In Figure 6, which represents a chromosome, an element of the array indicates a city and an indicator shows the order of a tour. To calculate the distance between two fireflies by using the distance between two cities, it can be obtained from the following formulae:

$$\beta(r) = \beta_0 e^{-\gamma r^2}, \tag{32}$$

$$r = 10 \times \frac{A}{N}, \tag{33}$$

where, r is the distance, A is the number of arcs, and N is the number of cities [14]. If $\gamma \to 0$, $\beta = \beta_0$; hence, the firefly's attractiveness value is close to zero (if it is seen by the other firefly); if $\gamma \to \infty$, $\beta = 0$; it means that the firefly moves in a random route and the other firefly has not seen it [59]. In this paper, γ is in the interval [0.01, 0.15] [58].

3. Computational results

We analyze the results of this research through different aspects described in four parts (representation of objective function conflict, evaluation of the efficiency of meta-heuristic algorithms, performing time analysis, and identification of evaluation metrics and comparison of two objective meta-heuristic algorithms).

3.1. Representation of objective function conflict

In this section, we investigate the conflict between objective functions. In Figure 7, for a problem with 4 depots and 10 affected points, the Pareto solutions obtained from ε-constraints are represented. According to the figure, by increasing the second objective function values (i.e., maximization of reliability), values

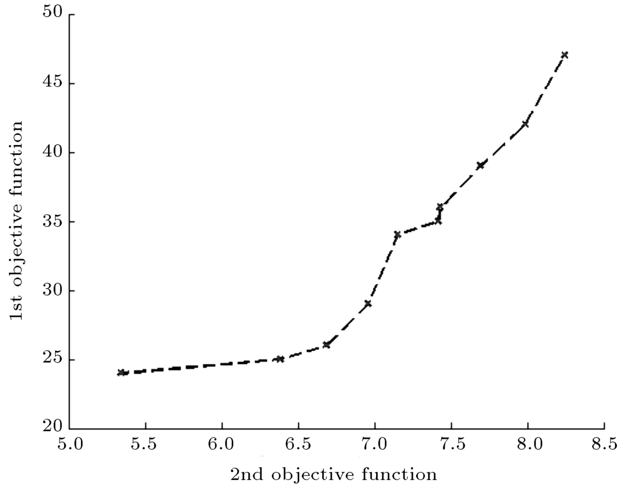

Figure 7. Representation of the Pareto solutions in the ε-constraint method and objective function conflict.

of the first objective function (i.e., minimization of the maximum transportation time) increase. By increasing an objective function, the other objective function is reduced (otherwise, the two objective functions are in conflict with each other).

3.2. Evaluation of the efficiency of meta-heuristic algorithms

In this section, in order to obtain the performance of the proposed GA and FA, the results for 10 problems with different dimensions are compared with the results of GAMS (ε-constraint method). The best values of objective functions and the errors of GA and FA in comparison with the ε-constraint method are given for each problem in Table 4. The solving time of the ε-constraint method is considered up to 3600 seconds. The row shown with a dash in the table indicates that GAMS is not capable to solve the problem within the time limit (i.e., 3600 seconds). For each of the two objective functions, the GA's error in comparison with the ε-constraint method is obtained from the following equations. The error of the FA algorithm is similarly calculated by:

$$Gap_{OF_1} = \frac{OFV1_{\text{NSGAII}} - OFV1_{\varepsilon\text{–constraint}}}{OFV1_{\varepsilon\text{–constraint}}} * 100, \tag{34}$$

$$Gap_{OF_2} = \frac{OFV2_{\text{NSGAII}} - OFV2_{\varepsilon\text{–constraint}}}{OFV2_{\varepsilon\text{–constraint}}} * 100. \tag{35}$$

As it can be seen from Table 4, the mean differences between the values of the GA and ε-constraint method are 2.87% and 6.17% for the first and second objective functions (i.e., transportation time and reliability, respectively). Additionally, the mean differences between the best values of the FA and ε-constraint method are 2.4% and 6.24% for the first and second objective functions, respectively. Thus, we conclude that the

Table 4. Comparison of the best values of the ε-constraint method, NSGA-II and MOFF.

(Problem no., depots, affected areas)	ε-constraint		NSGA-II		Gap (%)	MOFF		Gap (%)
	(Best OFV2, best OFV1)	CPU time	(Best OFV2, best OFV1)	CPU time	(OFV1, OFV2)	(Best OFV1, best OFV2)	CPU time	(OFV1, OFV2)
(1, 2, 5)	(24.3, 3.7)	7	(24.3, 3.7)	10	(0.00, 0.00)	(24.3, 3.7)	11	(0.00, 0.00)
(2, 3, 10)	(31.2, 5.4)	11	(31.8, 5.2)	12	(1.92, 3.70)	(31.6, 5.1)	11	(1.28, 5.56)
(3, 4, 9)	(33.9, 7.0)	19	(35.9, 6.9)	21	(5.90, 1.43)	(34.4, 6.9)	15	(1.47, 1.43)
(4, 3, 12)	(22.3, 10.8)	31	(22.7, 10.7)	44	(1.79, 0.93)	(23.1, 10.8)	39	(3.59, 0.00)
(5, 5, 14)	(56.6, 11.9)	185	(57.8, 10.8)	72	(2.12, 9.24)	(58.1, 10.5)	61	(2.65, 11.76)
(6, 6, 15)	(55.9, 13.9)	563	(57.4, 12.4)	124	(2.68, 10.79)	(57.1, 13.2)	82	(2.15, 5.04)
(7, 7, 17)	(45.9, 15.5)	795	(47.9, 13.9)	158	(4.36, 10.32)	(47.7, 14.1)	114	(3.92, 9.03)
(8, 8, 18)	(46.1, 16.1)	1502	(48.2, 14.5)	198	(4.56, 9.9)	(48.1, 14.3)	187	(4.34, 10.65)
(9, 9, 19)	(58.2, 17.3)	2105	(59.2, 15.7)	236	(1.72, 9.25)	(59.5, 15.1)	205	(2.23, 12.72)
	(–, –)	–	(59.6, 17.6)	323	(–, –)	(59.8, 16.5)	297	(–, –)
Average	(41.6, 11.4)	579.8	(44.5, 11.1)	116.8	(2.78, 6.17)	(44.4, 11.0)	102.2	(2.40, 6.24)

mean gaps of two objective functions with these meta-heuristic algorithms are very small and, therefore, they are efficient.

3.3. Analysis of the solving time

Figures 8 and 9 compare the problem-solving time of the ε-constraint method with the solving time of each of the meta-heuristic algorithms.

As it can be seen from the two figures, by growing the dimensions of the problem, solving time of ε-constraint method exponentially increases while solving time of Meta Heuristic algorithms increases with a mild slope.

3.4. Evaluating metrics and comparing two objective meta-heuristics

In multi-objective optimization problems, the problem solutions constitute an optimal Pareto front. The per-

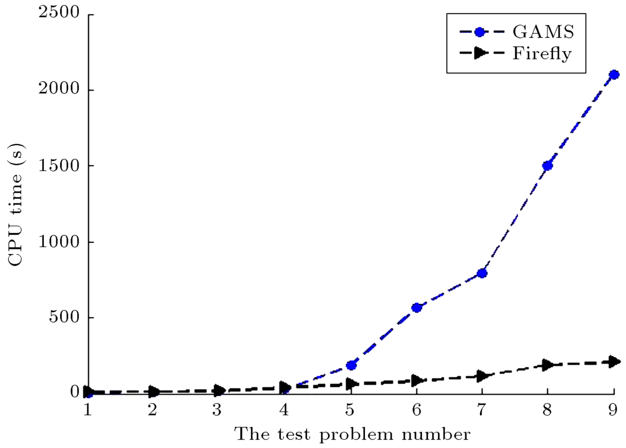

Figure 8. Problem-solving time of the ε-constraint method in comparison with the firefly algorithm.

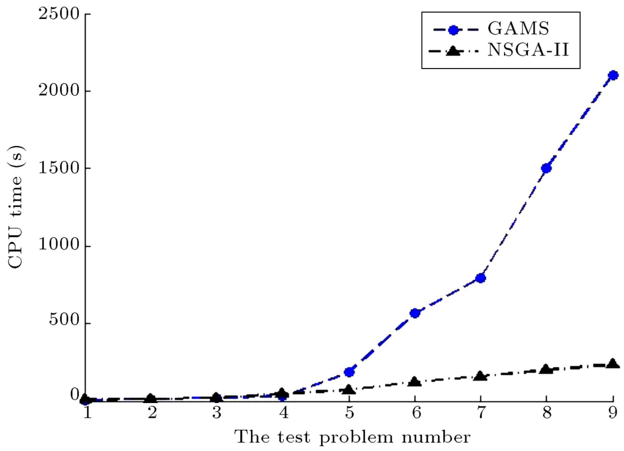

Figure 9. Problem-solving time of the ε-constraint method in comparison with the genetic algorithm.

formance of different algorithms that produce Pareto front can be compared with a different method. In this part, the metrics used in this study are briefly explained. In many studies, a number of Pareto solution metrics are used as quantitative metrics of the algorithm performance. As the number of a Pareto solution of a method is more, it is more desirable. The spacing metric, as another metric that computes the relative spacing of consecutive solutions, was introduced by Scott [61]. Smaller values of this metric are better. This metric is defined by:

$$SM = \frac{\sum_{i=1}^{N-1} |\bar{d} - d_i|}{(N-1)\bar{d}}, \tag{36}$$

where N is the number of Pareto solutions, d_i is the spacing between two sequential solutions in optimal front obtained by each algorithm, and d is the average

Table 5. Characteristics of the generated test problems.

Helicopter	Truck	Vehicle depot	Affected point in cluster 2	Affected point in cluster 1	Problem no.
2	3	6	5	7	1
2	3	6	7	10	2
2	4	8	9	15	3
2	4	7	7	16	4
3	5	7	8	18	5
3	6	8	8	20	6
3	6	8	10	24	7
4	5	9	11	25	8
4	7	9	15	30	9
5	7	9	16	33	10
5	9	9	20	35	11
5	9	10	30	40	12
5	10	12	30	45	13
5	12	15	35	50	14

Table 6. Values of evaluation metrics for GA and FA.

Problem no.	NSGA-II				Firefly			
	SM	DM	NOPS	Run time	SM	DM	NOPS	Run time
1	0.7722	8.7285	6	16	0.2468	7.4540	5	19
2	0.7430	7.8174	5	23	0.7131	8.4786	6	21
3	0.7476	8.4234	1	47	0.4012	9.0088	7	26
4	0.6247	4.4338	2	48	0.1708	2.6671	3	51
5	0.4357	6.5239	3	67	0.4197	6.3255	5	47
6	1.0670	7.6869	4	103	0.2408	6.4235	5	77
7	0.0459	3.2440	5	120	0.5315	3.9300	4	103
8	1.3674	7.0100	6	126	0.4920	8.8432	7	163
9	1.0334	6.9375	7	351	0.2513	6.8689	5	266
10	0.3656	7.0629	8	429	0.1175	3.8612	6	298
11	0.5401	7.6195	9	529	1.0334	6.9375	6	528
12	0.5881	6.0165	1	754	0.6296	6.8249	5	656
13	0.2265	6.4641	1	1447	0.0071	6.7354	4	1259
14	0.5540	4.9819	1	2226	0.4560	6.8386	5	1953
Average	0.6508	6.6393	4	449.4076	0.4080	6.5141	5	391.0351

of d_is. The diversity metric is another metric applied in comparison of algorithms. Diversity metric measures the variety of the Pareto front and larger values of this metric are better [62]:

$$DM = \sqrt{\left(\frac{\max f_{1i} - \min f_{1i}}{f_{1,\text{total}}^{\max} - f_{1,\text{total}}^{\min}}\right)^2 + \left(\frac{\max f_{2i} - \min f_{1i}}{f_{2,\text{total}}^{\max} - f_{2,\text{total}}^{\min}}\right)^2}. \quad (37)$$

To compare the performances of the proposed algorithms, 14 problems with different sizes are produced and the evaluation metrics of two meta-heuristic algorithms are presented for each problem. The attributes of the given problems and the parameters' values are given in Tables 5 and 6. It is worth mentioning that the number of the ground vehicle is between 3 and 12 and the number of the air vehicle is between 2 and 5 in given problems. In all problems, there is one depot for air vehicles. Also, the values of the capacity parameter come from a uniform distribution, U (50, 60), and the values of transportation time are selected from a uniform distribution, U (10, 60).

In the following, for better conception of the

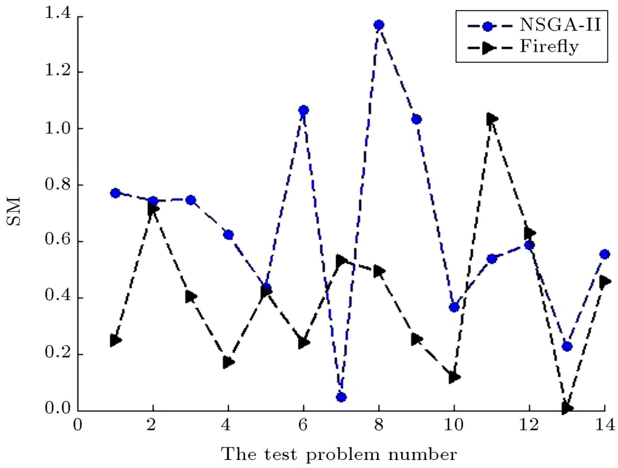

Figure 10. Comparison of GA and FA according to the spacing metric.

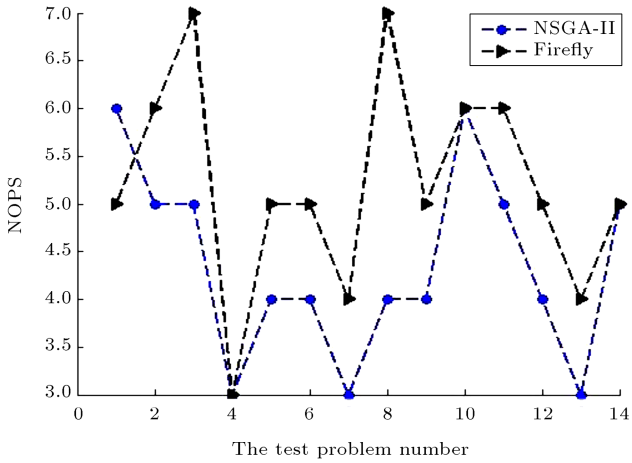

Figure 12. Comparison of GA and FA according to the number of Pareto solutions.

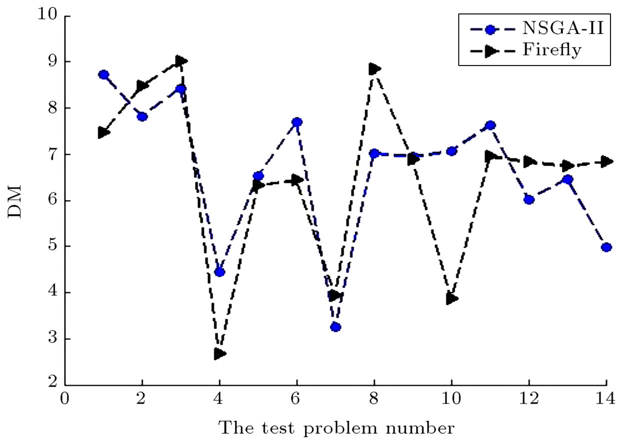

Figure 11. Comparison of GA and FA according to the diversity metric.

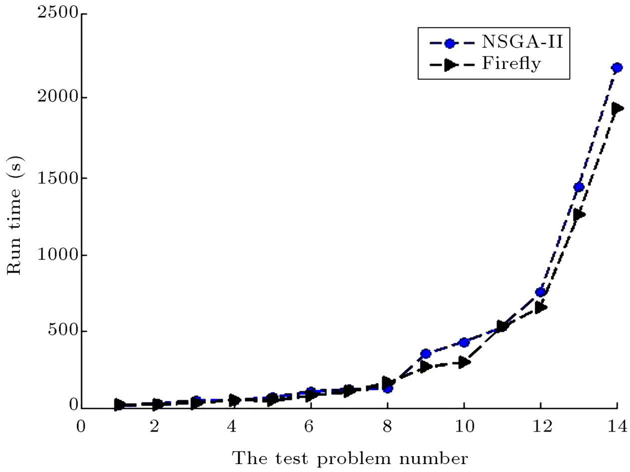

Figure 13. Comparison of GA and FA according to the solving time.

performance of meta-heuristic algorithms, the computational results of comparison metrics are depicted.

Figure 10 compares two meta-heuristic algorithms in terms of the distance metric. It can be said that the FA in most cases has better performance than GA. Figure 11 presents the diversity metric for the problems solved by using two algorithms. There is not any particular trend in this figure. Figure 12 is related to the metric of the number of Pareto solutions. According to this figure, in terms of the number of the Pareto solution metric, the FA has more desirable performance than GA. Finally, Figure 13 compares the solving times of two algorithms, indicating the better performance of FA.

4. Conclusion and recommendations

In this paper, a heterogeneous multi-depot multi-objective vehicle routing model was developed. Because the routing problem of this paper was considered in multi-mode distribution, the affected points were clustered by using the ANFIS method, which was an integration of neural and fuzzy networks, according to affecting criteria on relief distribution operations at the time of crisis. Accordingly, the clusters consisting of ground or air relief or both were specified. Then, for each cluster, the affected points of each cluster were prioritized by using the permanent matrix, according to the affecting factors on the route reliability. In this study, NSGA-II and MO Firefly were proposed for solving essential commodity distribution model in the response phase, and the efficiency of these algorithms was evaluated in solving the problems with different sizes. The results showed that for this routing problem, the MO Firefly gave better solutions than NSGA-II did. Distribution of several commodities in multiple periods by use of heterogeneous vehicles by assuming uncertain demands for the affected points can be our suggestion for future studies. Using different meta-heuristic algorithms and comparison of them is another suggestion.

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