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Research Article

Planning for Medical Emergency Transportation Vehicles during Natural Disasters

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Abstract

One of the main critical steps that should be taken during natural disasters is the assignment and distribution of resources among affected people. In such situations, this can save many lives. Determining the demands for critical items (i.e., the number of injured people) is very important. Accordingly, a number of casualties and injured people have to be known during a disaster. Obtaining an acceptable estimation of the number of casualties adds to the complexity of the problem. In this paper, a location-routing problem is discussed for urgent therapeutic services during disasters. The problem is formulated as a bi-objective Mixed-Integer Linear Programming (MILP) model. The objectives are to concurrently minimize the time of offering relief items to the affected people and minimize the total costs. The costs include those related to locations and transportation means (e.g., ambulances and helicopters) that are used to carry medical personnel and patients. To address the bi-objectiveness and verify the efficiency and applicability of the proposed model, the ε-constraint method is employed to solve several randomly-generated problems with CLEPX solver in GAMS. The obtained results include the objective functions, the number of the required facility, and the trade-offs between objectives. Then, the parameter of demands (i.e., number of casualties), which has the most important role, is examined using a sensitivity analysis and the managerial insights are discussed.

***Keywords**:* Medical emergency services; Disaster; Location-routing; Mixed-Integer Linear Programming; ε-constraint method.

1. Introduction

In today's world, despite the dramatic growth of technology, natural disasters (e.g., earthquake, flood, fire and volcano eruption) and manmade disasters (e.g., wars, terrorist attacks and industrial accidents) are major obstacles for growth and developments of nations. Lack of preparation for dealing with such incidents imposes heavy damages on nations and their assets. Although emotional and financial damages caused by such events cannot be completely compensated, effective planning can significantly reduce damages. Since the scale and severity of such events are usually large, the level of demands in such situations is high. To respond to such emergencies, large-scale relief operations must be conducted. In normal conditions, relief agencies can respond to small-scale events. However, in the majority of cases, such agencies do not have the necessary tools and resources to respond quickly to large-scale disasters (Jahre et al., 2007).

Generally, the humanitarian relief chain aims to offer emergency services to people in disaster and to minimize the number of fatalities by an effective distribution of resources (Tofighi et al., 2015). Since the amount of demands in such conditions is not definite and known, coordination in this chain is a complex and challenging task. Furthermore, there may be some potential dangers during the operation of offering relief services to the affected people (Balcik et al., 2010). This problem is intensified when local infrastructures have been destroyed and the amount of resources is limited (Balcik and Beamon, 2008). Logistics operations during the disaster include several sub-operations, such as evaluation, provision, transportation, keeping and distribution of goods and equipment, and other services that need to be offered to the people. The crucial items have to be delivered within the shortest time using the best possible locations to the people affected by the crisis. This task must be performed accurately based on effective planning to respond to the urgent demands of the people (Özdamar et al., 2004).

Establishing an effective and scientific system for the logistics operation of disaster management is a critical issue. In such a system, the duties of all sub-systems must be defined in advance (Douglas, 1997). Improvements in logistics operations and relief chains assist to offer relief support to people within the shortest time (Balcik and Beamon, 2008). Sending critical items, serving medical first aids, and transferring injured people to emergency centers (e.g., hospitals and temporary infirmaries) are very critical for reducing the number of fatalities and disabilities in such situations. This is particularly the case in the first 72 hours of emergency conditions. Since some resources such as ambulances and helicopters are not easily accessible, planning for these situations is very difficult and challenging.

According to Talarico et al. (2015), the process of responding to emergency conditions includes three steps:

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1) identifying those areas whose needs must be met immediately, 2) classification of demands based on severity and urgency, and 3) solving the routing problem and scheduling of vehicles. Since degrees of injury among the affected people are not identical, they must be classified based on priorities. This is called triage. Initially, the concept of triage was used for war-affected zones and areas influenced by natural disasters. Later, it was utilized for other environments such as urgency centers in the hospitals, because injured people were taken to hospitals without any pre-planning and pre-defined timetable. In the triage mechanism, each group of injured people is defined by a color: red, orange, yellow, green, and blue. Also, an urgent time is defined for each group of injured people. If a proper response to the needs is not provided during this time, the probability of death increases. For example, those suffering from breathing problems and also those injured people in the neck and head are classified in the red group. The emergency time for this group is 10 minutes. In natural disasters, the triage system must be used for disaster management. For problem simplification, injured people can be divided into two general groups: those who can be treated at the site and those who must be transferred to the hospital (Talarico et al, 2015).

Since the service time during a disaster is very limited, the distribution of resources among affected people should be carried out optimally. The process of service includes the treatment of outpatients and the transfer of more serious cases to hospitals. An important point to note during the disaster is that emergency vehicles should avoid fuel shortages. This is a problem that may seriously disrupt relief operations. This problem can be avoided by proper fuel planning. Barbarosoğlu et al. (2002) presented a model for relief operation by the Turkish army during a disaster. They discussed the impact of such an operation on reducing the time of supporting the affected people during a disaster.

This paper presents a model for relief support planning in urban areas during a disaster. In this problem, there is a group of injured people with different degrees of severity. The relief system includes ambulances and helicopters. This study aims is to find a proper plan for emergency vehicles. In the first phase of the planning, the best location for emergency vehicles and temporary infirmaries are determined, and in the second phase, optimal routes and refueling planning for vehicles are determined to complete the process of servicing injured people considering different severities of injured people within the shortest possible time and real-world restrictions. New issues addressed in the present study are concerned with the main decisions taken in offering relief support. This includes making decisions on the locations of transportation centers and temporary hospitals, finding the optimal routes for vehicles, minimizing the time of responding to the demands, and planning for vehicles refueling. Since the time of transporting people from the affected areas to hospitals is critically important and the shortage of fuel may disrupt transportation operation, planning for vehicles refueling is a very crucial issue.

In Section 2, the literature in this field is reviewed. In Section 3, the problem is described and a mathematical model for its solution is suggested. Section 4 provides the computational results for the model. At last, conclusions and some suggestions for future studies are presented in Section 5.

2. Literature Review

The first serious studies on transportation during the disaster were conducted by Knott (1987), whose study focuses to fulfill the customers' demand by employing the available vehicles in the warehouse. Barbarosoğlu et al. (2002) developed an emergency relief model considering the aerial mode of transportation. The problem consists of two stages. In the first stage, decisions are made on fleet management, flights, and the number of flights. In the second stage, operational decisions such as optimal routes, rescue, and refueling are taken. Özdamar et al. (2004) conducted a study on logistics planning considering a disastrous situation. They developed a network to define a dynamic time-dependent transportation problem for generating optimal solutions within given time intervals repeatedly. Özdamar (2011) focused on the planning of helicopters in disasters (for transferring injured people, medicines and urgent commodities). The model minimizes the total servicing time of injured people. Also, the loading time was considered in the proposed model.

Doerner et al. (2007) studied the possibility of minimizing total uncovered demand in a disaster using covering tours. They presented a model in which a central depot, a fleet of vehicles, and a set of potential medical service centers were considered. In this model, the optimal routes of vehicles should be determined to have in time delivery of required items. Moreover, demand points are considered small villages with a low population and a short distance from each other. The problem was solved by a heuristic algorithm based on TSP assumptions, and the obtained results were compared. Nolz et al. (2010) presented a bi-objective model for dispatching medicines and foods and providing shelters for regions affected by the disaster. They employed a genetic algorithm based on the neighborhood search algorithm. This algorithm was used for real data of an earthquake in Ecuador. Then, it was compared with the ε constraint method.

Huang et al. (2012) studied models of routing and resource assignment to relieve injured people during a disaster. They introduced three critical factors for routing and resource assignment during a disaster: efficiency, usefulness, and equal enjoyment. To consider these factors, they presented a basic mathematical model with different objective functions. They defined efficiency as the minimization of the costs of routing and resource provision. Usefulness was defined as the minimization of the time of sending the needed items to the affected people. Equal enjoyment was defined as the minimization of differences among the services offered to the affected people. These three objectives were examined in similar problems, and the outputs for each criterion were obtained.

Wohlgemuth et al. (2012) presented a model for dynamic routing in pre-disaster conditions. In the proposed model, it was assumed that relief items can be sent to any point in the affected area. They showed that the model could shorten the period of loading and unloading. In the given model, the travel time between two points was dynamic (some routes were impassable) and the objective is to minimize the time of sending a single item by several vehicles. Azimi et al. (2012) presented a model for locating intermediate relief points (stations) and the routing. They declared that relief equipment cannot visit all these stations. Therefore, relief points must be in the nearest points so that people in all affected areas can have access to the needed items. Relief centers must be established at the proper points to keep all demand points in a distance shorter than the maximum allowable distance from a relief station. In their model, necessary items are sent from a central depot by homogeneous vehicles to the affected areas. Their model aimed to minimize the distance that must be covered by each vehicle. They applied a heuristic algorithm to solve the model, and its efficiency was compared with the exact method.

Some research works are reviewed as follows to clarify the importance of the basic problem related to Location-Routing Problems (LRPs). A location-routing model was studied by Walter and Gutjahr (2014) in which emergency relief was planned for injured people. They concluded that temporary intermediate warehouses play a highly significant role to fulfill the necessities of the affected people in the minimum time possible. A triple-objective model was also suggested to minimize short- and mid-term costs and maximize the quantity of dispatched humanitarian commodities. To solve the model, the ε-constraint method was employed and compared to Variable Neighborhood Search (VNS).

Abounacer et al. (2014) conducted a similar study, in which the optimal number of relief centers and humanitarian aid distribution were determined. Also, the optimal routes for transferring aids from distribution centers to demand points were introduced. The problem had three contradictive objectives: minimizing the total transferring time, minimizing the number of centers and minimizing the quantity of unmet demands. Two constraints were included in the problem: firstly, the travel time between two certain points had to be less than a certain period and secondly, the capacities of different vehicles were different. Every vehicle in every travel visited one demand point. Then, it returned to its original distribution center or another center. Finally, by employing the ε-constraint method, the Pareto-optimal solutions were presented for randomly generated problems.

Halskau (2014) studied a routing problem for marine helicopters to minimize the number of victims during a disaster. Since helicopter flight might be disrupted by potential dangers, a proper plan of routing was found to minimize the number of fatalities. In this problem, aids were transferred through hubs. In this case, naval facilities were hubs. Based on the findings of this study, using several hubs instead of one hub was more effective for relief operations. Knyazkov et al. (2015) presented a model to find the optimal routes for transferring injured people by ambulances in Saint Petersburg. Their goal was to reduce the transferring time of injured people by presenting the optimal route. They concluded that the traffic condition highly affects the decision-making process and may change all the routes and decisions.

Another study on health emergency services was done by Chen and Yu (2016). According to the demand level in a disastrous situation, a location-routing problem was presented to heighten the servicing level. For this purpose, an integer programming model and a graph network were developed to determine the optimal locations of facilities, and Lagrange’s method was employed for solving the problem. Ultimately, they tested the model by conducting a case study. By reviewing the literature, it is demonstrated that the problem of simultaneous routing for ambulances and helicopters has rarely been studied. Also, the problem of minimizing the time to reach the final point of the route has not been properly addressed. Another issue neglected in the literature is planning for vehicles refueling in the operation zones. Maghfiroh et al. (2018) proposed a dynamic Vehicle Routing Problem (VRP) for the last mile distribution during a disaster. They developed a modified Simulated Annealing (SA) and VNS algorithm to solve the problem and minimize the total traveling time.

An improved shuffled frog leaping algorithm (SFLA) was employed by Duan et al. (2018) to investigate the dynamic emergency vehicle dispatching problem. They regarded response time, accident severity, and accident time windows as the main factors to propose an emergency vehicle dispatching model.

Zhang et al. (2018) introduced a sustainable multi-depot LRP by taking into account the uncertain information. They concurrently considered the travel time, emergency relief costs, and CO_2 emissions in their model via the uncertainty theory. A hybrid Genetic Algorithm (GA) and uncertain simulations were used to solve the problem. An integrated Location-Inventory-Routing Problem (LIRP) was suggested for pre- and post-disaster management by Tavana et al. (2018). They proposed a multi-echelon humanitarian logistics network to provide an appropriate flow of relief products. The problem was solved by an improved Non-dominated Sorting Genetic Algorithm (NSGA-II) algorithm. According to the discussed literature so far, the proposed model in this paper considers vehicles refueling and the use of helicopters together with ambulances. Liu et al. (2018) developed an RO model for relief logistics planning considering uncertain demands and transportation time. The model was applied to a case study problem in a city in China that had recently suffered from an earthquake. The authors proposed optimal management policies using sensitivity analyses.

The contributions of the current study are explained as follows. After reviewing the background of the research, it is clarified that considering the concurrent transportation planning of ambulances and helicopters has not been investigated adequately. On the other hand, there has been a lack of attention to response time as the main objective against the total cost minimization. Moreover, time plays a critical role in providing relief services. More importantly, during a disaster, ambulances as the main service-providers should not be confronted with fuel supply issues as this disrupts the relief operations and increases the response time. This subject has not been taken into account in most studies as well. Furthermore, the effect of a second objective (i.e., total cost) is analyzed to provide a trade-off between time-oriented and cost-oriented objectives. To this end, an exact solution technique (i.e., the ε-constraint method) is employed and the model is implemented in CPLEX solver of GAMS software to obtain the Pareto fronts. Finally, a sensitivity analysis is performed to investigate the behavior of the objective functions in response to the changes in parameters and managerial insights and decision are provided.

3. Problem Description

Suppose there is a graphical network of regular hospitals, potential temporary hospitals, transfer points, ambulance stations, helicopter stations, demand points, and refueling stations. The number of these locations is determined at the beginning. Such a network is created in the operation area during a disaster when a large number of injured people are waiting to receive treatment. Also, a fleet of heterogeneous vehicles with certain capacities are used. Emergency vehicles are sent from stations to affected areas. Based on the severity level of injured people, injured people may need to be treated at the site or transferred to the hospital. During relief operation, planning is made for vehicles refueling. In the real world, helicopters are responsible for transferring severely injured people to the treatment centers and ambulances are in charge of both treating at the site and transferring injured people to the treatment centers. The aim of solving this problem is to find the optimal locations for relief facilities, find the best routes for vehicles, minimize costs of operation, and shorten the time of operation. These had to be done by this objective that all affected people receive services.

The general structure of the relief network is shown in Figure 1. In this figure, red points show that injured people in that point belong to the red group (i.e., severe injured people), the green points show that inured people belong to the green group, blue circles are ambulance stations, blue triangles are transfer points, blue hexagons denote potential temporary hospitals, blue squares represent regular hospitals, blue triangles express helicopter stations, and blue dodecagons show petrol stations.

In this problem, the following assumptions are considered.

1. The distance between different points of the network is given.
2. Ambulances and helicopters have limited capacity for providing services for patients.
3. Ambulances have limited fuel consumption.
4. There are several potential points for the construction of temporary hospitals and transfer points.
5. Patients are divided into two groups of green and red.
6. Each ambulance can carry one or more red patients up to its capacity to the hospitals or transfer points.
7. Each ambulance can initially handle a green-type patient and then carry the red-type patient to the hospital or the transfer point.
8. Hospitals have sufficient capacity to service all the red-type patients.
9. The number of patients after the incident is uncertain.
10. A hard time window is defined for each of the affected areas (demand point).
11. Each helicopter should land at a transfer station and then transfer patients to hospitals.

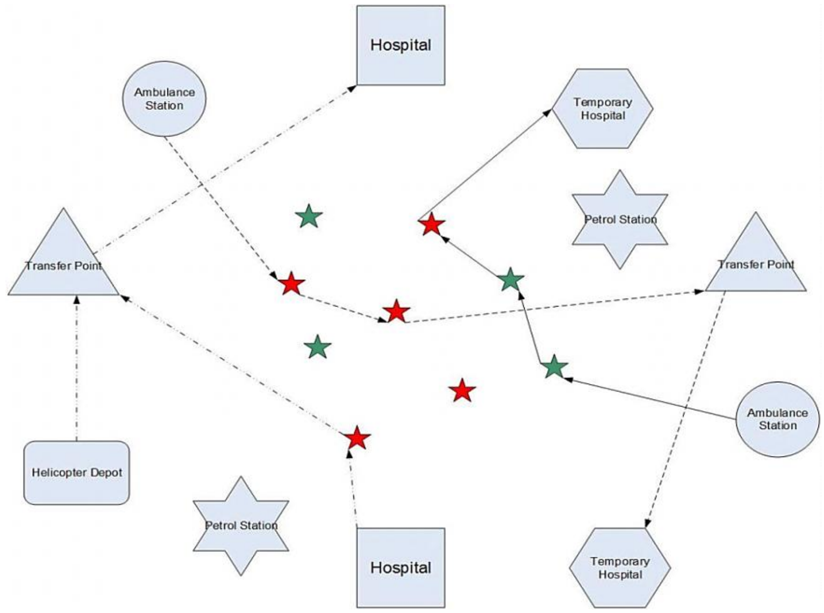

Fig. 1. Relief network.

3.1. Mathematical model

The proposed mathematical model of the problem is defined by using the following notations:

Sets and indices:

I	Set of total points
H	Set of regular hospitals
TP	Set of transfer points
TH	Set of temporary hospitals
WS	Set of ambulance stations
HS	Set of helicopter stations
AA	Set of affected areas that demand some items
FP	Set of petrol stations
K	Set of ambulances
HC	Set of helicopters
$i, j, j1, j2$	Indices
k	Index of ambulances
h	Index of helicopters

Parameters:

t_{ij}	Travel time between *i* and *j*
QA_k	Capacity of ambulance *k*
QH_h	Capacity of helicopter *h*
UT_k	The available time for using ambulance *k*
DR_i	Number of injured people belonging to the red group at point *i*
DG_i	Number of injured people belonging to the green group at point *i*
ST_i	Time of service to injured people belonging to the green group at point *i*
$F1_k$	Initial fuel of ambulance *k*
$F2_k$	The fuel of each ambulance after being refueled in petrol stations
E_i	The lower boundary of the time window for injured people belonging to the red group at point *i*
L_i	The upper boundary of the time window for injured people belonging to the red group at point *i*
HCP_{hi}	A binary parameter: 1 if helicopter *h* is in the helicopter station *i* at the start time
α	Transformation coefficient of the time spent to consume fuel by ambulances
cx_{ij}	Travelling cost from *i* to *j* by an ambulance
cy_{ij}	Travelling cost from *i* to *j* by a helicopter
f_i	Establishment cost for the transfer center *i*
$f1_i$	Establishment cost for the temporary hospital *i*

Decision variables:

P_{ki}^S	1 if ambulance *k* is at station *i* at the beginning of the movement; 0, otherwise
P_{ki}^H	1 if ambulance *k* is in hospital *i* at the beginning of the movement; 0, otherwise
y_i	1 if transfer center *i* is established; 0, otherwise
yy_i	1 if temporary hospital *i* is established; 0, otherwise
x_{ijk}	1 if ambulance *k* travels the path between points *i* and *j*; 0, otherwise
z_{ijh}	1 if helicopter *h* travels the path between points *i* and *j*; 0, otherwise
ff_{ki}	Remaining fuel in ambulance *k* at the arriving time at point *i*
t_{ki}^{arrive}	Time spent for ambulance *k* to arrive at point *i*
t_{ki}^{left}	Time when ambulance *k* leaves point *i*
cx_{ki}	Number of injured people (group red) transferred from point *i* by ambulance *k*
rx_{ki}	Number of injured people (group red) transferred to transportation center *i* by ambulance *k*
hx_{ki}	Number of injured people (group red) transferred to hospital *i* by ambulance *k*
hg_{ki}	Number of injured people (group green) treated by ambulance *k* at the point *i*
nx_{ijh}	Number of injured people (group red) transferred from point *i* to hospital *j*

Mathematical Formulation:

$$\text{Min } W1 = \max\{t_{ki}^{left}\} \tag{1-1}$$

$$\text{Min } W2 = \sum_i \sum_j \sum_k cx_{ij} x_{ijk} + \sum_i \sum_j \sum_h cy_{ij} z_{ijh} + \sum_i f_i y_i + \sum_i f1_i yy_i \tag{1-2}$$

s.t.

$$\sum_{i \in WS} P_{ki}^S + \sum_{i \in H} P_{ki}^H = 1, \qquad \forall k \in K \tag{2}$$

$$\sum_{j \in I} x_{ijk} \leq P_{ki}^S \;\;, \;\; \forall i \in WS, k \in K \tag{3}$$

$$\sum_{j \in I} x_{ijk} \leq P_{ki}^H \;\;, \;\; \forall i \in H, k \in K \tag{4}$$

$$\sum_{j\in I} x_{iik} = 0 \ , \forall k \in K \tag{5}$$
$$\sum_{i\in I} x_{ijk} - \sum_{i\in I} x_{jik} = 0, \quad \forall j \in I \tag{6}$$
$$\sum_{i\in I} x_{ij1k} - \sum_{i\in I} x_{ij2k} = 1 \ , \ \forall j1 \in TP, j2 \in H \tag{7}$$
$$ff_{ki} = F1_k \, P_{ki}^{S} \ , \forall i \in WS, k \in K \tag{8}$$
$$ff_{ki} = F1_k \, P_{ki}^{H} \ , \forall i \in H, k \in K \tag{9}$$
$$ff_{ki} - \alpha t_{ij} = ff_{kj} + M(1 - x_{ijk}), \quad \forall i, j \in I, k \in K \tag{10}$$
$$ff_{kj} = F2_k \sum_{i\in I} x_{ijk} \quad , \forall j \in FP, k \in K \tag{11}$$
$$t_{kj}^{arrive} = t_{ki}^{arrive} + t_{ij}(1 - x_{ijk}), \quad \forall i, j \in I, \quad k \in K \tag{12}$$
$$\sum_{k\in K} cx_{ki} \geq DR_i \qquad \forall i \in AA \tag{13}$$
$$\sum_{k\in K} rx_{ki} \leq My_i \qquad \forall i \in TP \tag{14}$$
$$\sum_{i\in I} x_{ijk} \leq My_j \ , \forall j \in TP, k \in K \tag{15}$$
$$\sum_{i\in AA} cx_{ki} = rx_{kj} \sum_{i\in I} x_{ijk} \quad , \quad \forall j \in TP, k \in K \tag{16}$$
$$\sum_{i\in AA} cx_{ki} = hx_{kj} \sum_{i\in I} x_{ijk} \quad , \quad \forall j \in H \cup TH, k \in K \tag{17}$$
$$t_{ki}^{left} = t_{ki}^{arrive} + ST_i \, hg_{ki} \quad , \quad \forall i \in AA, k \in K \tag{18}$$
$$\sum_{k\in K} hg_{ki} = DG_i, \quad \forall i \in AA \tag{19}$$
$$\sum_{k\in K} cx_{ki} \leq QA_k \qquad \forall i \in AA \tag{20}$$
$$\sum_{i\in HS} z_{ijh} \leq y_i \ , \qquad \forall j \in TP, h \in HC \tag{21}$$
$$\sum_{i\in TP\cup HS} z_{ijh} - \sum_{i\in TP\cup H\cup TH} z_{ijh} = 0, \ \forall j \in TP, h \in HC \tag{22}$$
$$\sum_{i\in HS} \sum_{j1\in H\cup TH} z_{ij1h} = \sum_{i\in HS\cup TP} z_{ij2h} \ , \ \forall j2 \in TP, h \in HC \tag{24}$$
$$\sum_{i\in TP} \sum_{j\in H\cup TH} nx_{ijh} \leq QH_h, \quad \forall h \in HC \tag{25}$$
$$\sum_{h\in HC} \sum_{j\in H\cup TH} nx_{ijh} = \sum_{k\in K} rx_{ki} \ , \qquad \forall i \in TP \tag{26}$$
$$nx_{ijh} \leq Mz_{ijh} \ , \ \forall i \in TP, j \in H \cup TH, \qquad h \in HC \tag{27}$$
$$hx_{ki} \leq M \, yy_i \quad , \quad \forall i \in TH, k \in K \tag{28}$$
$$\sum_{i\in TP} nx_{ijh} \leq Myy_j \ , \forall \ j \in TH, \qquad h \in HC \tag{29}$$
$$\sum_{i\in I} \sum_{h\in HC} z_{ijh} \leq M \, yy_j \ , \ \forall j \in TH \tag{30}$$
$$P_{ki}^{S}, P_{ki}^{H} \ , y_i \ , yy_i \ , x_{ijk}, z_{ijh} \in \{0,1\}$$
$$ff_{ki}, t_{ki}^{arrive}, t_{ki}^{left}, t_{ki}^{left} \geq 0 \quad , cx_{ki}, rx_{ki}, hx_{ki}, hg_{ki}, nx_{ijh} \in Z^{+} \tag{31}$$

The first objective function (1-1) minimizes the maximum time required for ambulances to departure from the affected area. This objective aims to provide equity in allocating ambulances during the response phase besides improving the efficiency and effectiveness of services (Gutjahr and Nolz, 2016). The second objective function

(1-2) minimizes the total cost. This includes minimizing the cost of vehicle routing and finding locations for temporary hospitals and transfer centers.
According to Constraint (3), at the starting point, every ambulance is either at a hospital or one of the stations. According to Constraint (4), ambulances must start their trip from a station they belong to. Based on Constraint (4), ambulances must start their trip from the hospitals they belong to. As Constraint (5), a vehicle cannot directly return to its original point. Moreover, based on Constraint (6), when an ambulance reaches a certain point, it has to leave that point. According to Constraint (7), the destination of every ambulance is either a transfer station or a hospital. Constraints (8) and (9) the amount of fuel required for an ambulance to travel. Constraint (10) calculates the relation of fuel consumption in routes traversed by ambulances. Constraint (11) is related to refueling the ambulance at petrol stations. Constraint (12) shows the arriving time by ambulances in affected areas.
Constraint (13) shows that all injured people belonging to the red group must be transported from affected areas by ambulances. Constraint (14) states that if a transportation station is established, injured people belonging to the red group can be transferred there. Constraint (15) states that ambulances can go only to the established stations. Constraint (16) is related to the number of injured people (red group) in transfer stations. Constraint (17) is concerned with the number of injured people (red group) that are directly transferred to hospitals by ambulances. According to Constraint (18), the time required for an ambulance to leave a point is equivalent to the total of needed time to reach the destination and the servicing time at the site. According to Constraint (19), all injured people belonging to the green group must be treated. According to Constraint (20), each ambulance has a certain capacity. Also, regarding Constraint (21), helicopters can enter those transfer centers that have already been established.
According to Constraint (22), if a helicopter leaves a helicopter station or another transfer center, it goes to a certain transfer center and leaves that center for another transfer center or another hospital. Concerning Constraint (23), only those helicopters that stop in one of the transfer stations can go to hospitals. Constraint (24) expresses the capacity of helicopters. According to Constraint (25), all injured people (red group) transferred to transportation stations must be transported to hospitals by helicopters. Also, based on Constraint (26), if a helicopter does not stop in a transportation center, it cannot transport injured people from that point to another point. According to Constraints (27) and (28), injured people can be transferred to only temporary hospitals that have been already established. As Constraint (29), helicopters can go only to those temporary hospitals that have been already established. Constraints (30) and (31) show decision variables.

3.2. Linearization

Equation (1-1) and Constraints (16) and (17) make the suggested mathematical model non-linear. These equations can be linearized using the definition of the auxiliary variables (Gupte et al., 2013). In this way, a Mixed-Integer Linear programming (MILP) model can be obtained.
A binary variable of ρ_{ki} is defined to linearize Equation (1-1). Thus, we have:

$$W1 = \max\{t_{ki}^{left}\} \tag{1-1}$$

$$W1 - t_{ki}^{left} \geq -M(1-\rho_{ki}) \quad \forall i \in AA, k \in K \tag{32}$$

$$W1 - t_{ki}^{left} \leq \quad M(1-\rho_{ki}) \quad \forall i \in AA, k \in K \tag{33}$$

$$t_{kj}^{left} \leq t_{ki}^{left} + M(1-\rho_{ki}) \quad \forall i, j \in AA, k \in K; i \neq j \tag{34}$$

$$\sum_i \rho_{ki} = 1 \qquad \forall k \tag{35}$$

$$\rho_{ki} \in \{0,1\} \quad \forall i \in AA, k \in K \tag{36}$$

For constraints (16) and (17), since the value of $\sum_{i\in I} x_{ijk}$ is equal to 1 or zero, the following transformation can be used.
According to constraint (16):

$$\sum_{i\in AA} cx_{ki} = rx_{kj} \sum_{i\in I} x_{ijk} \quad \forall j \in TP, k \in K \tag{16}$$

$$\sum_{i\in AA} cx_{ki} = vv_{kj} \quad , \forall j \in TP, k \in K \tag{37}$$

$$vv_{kj} \leq rx_{kj} \quad , \quad \forall j \in TP, k \in K \tag{38}$$

$$vv_{kj} \leq M \sum_{i\in I} x_{ijk} \; , \; \forall j \in TP, k \in K \tag{39}$$

$$vv_{kj} \geq rx_{kj} - M(1 - \sum_{i\in I} x_{ijk}) \quad \forall j \in TP, k \in K \tag{40}$$

$$vv_{kj} \in Z^+ \quad , \quad \forall j \in TP, k \in K \tag{41}$$

Referring to Constraint (17):

$$\sum_{i\in AA} cx_{ki} = hx_{kj} \sum_{i\in I} x_{ijk} \quad \forall j \in H \cup TH, k \in K \tag{17}$$

$$\sum_{i\in AA} cx_{ki} = vvv_{kj} \quad \forall j \in H \cup TH, k \in K \tag{42}$$

$$vvv_{kj} \leq hx_{kj} \quad \forall j \in H \cup TH, k \in K \tag{43}$$

$$vvv_{kj} \leq M \sum_{i\in I} x_{ijk} \quad \forall j \in H \cup TH, k \in K \tag{44}$$

$$vvv_{kj} \geq hx_{kj} - M(1 - \sum_{i\in I} x_{ijk}) \quad \forall j \in H \cup TH, k \in K \tag{45}$$

$$vvv_{kj} \in Z^+ \quad , \quad \forall j \in H \cup TH, k \in K \tag{46}$$

4. Solution Procedure

One of the important features in multi-objective optimization is the priority of objectives. Accordingly, the improvement in one of the objectives deteriorates the other objectives. This is shown by Pareto-optimal solutions. Therefore, the ε-constraint method is employed to solve the proposed bi-objective model. The following subsection describes this method.

The ε-constraint method is a popular method for solving problems with more than one objective. Pareto fronts are easily generated by the ε-constraint method (Mavrotas, 2009). One of the advantages of the ε-constraint method is its ability to generate the desired number of efficient Pareto solutions, which is impossible in the other methods, such as weighted sum method (Tirkolaee et al., 2019).

In the ε-constraint method, the objective function with the utmost impotence is considered as the Main Objective Function (MOF) and the other objectives are considered as new constraints of the problem. In other words, the ε-constraint method converts a multi-objective model to a single-objective model with extra constraints. For the proposed problem, the ε-constraint method is employed through Equations (47)-(49).

$$\text{Min } f_1(x) \tag{47}$$

$$x \in X \tag{48}$$

$$f_2(X) \leq \varepsilon_2 \tag{49}$$

...

$$f_n(X) \leq \varepsilon_n$$

In the proposed problem, we have:

$$\text{Min } f=f_1 \tag{50}$$

$$x \in X \tag{51}$$

$$f_2(X) \leq \varepsilon_2 \tag{52}$$

The first objective is the MOF. Main steps in the ε-constraint method are as follows:

1) Considering one of the objectives as the MOF,

2) Solving the problem based on each objective function, and then, the optimal values of objective functions are obtained.

3) Dividing the difference between two optimal values of the second objective function into several pre-determined parts. A table of values for $\varepsilon_2, \ldots, \varepsilon_n$ is then generated.

4) Solving the problem by the main objective function and $\varepsilon_2, \ldots, \varepsilon_n$.

5) Reporting the Pareto-optimal solutions.

5. Numerical Results

In this section, random samples are produced and the data of each sample are described. The problem was solved by GAMS (version 24.1) and CPLEX solver. The validity of the model was tested by solving the samples. In the ε-constraint method, six breakpoints were considered for each objective function. Six Pareto points for each of the problems were generated in total.

To produce a sample problem at a small size (P1), medium size (P2), and large size (P3) in two-dimensional space, *n* points were examined: points of regular hospitals, points of potential temporary hospitals, points of transfer stations, points of ambulance stations, points of helicopter stations, points of affected areas (demand points), and points of petrol stations. In defining some parameters, uniform distribution was used. These are shown in Table 1. In Table 2, the first column is related to random samples, the second column includes several points in graph network, the third column represents the number of ambulances, the fourth column indicates the number of helicopters, the sixth column indicates the number of regular hospitals, the seventh column presents the number of potential temporary hospitals, the eighth column indicates the number of transfer stations; the ninth column represents the number of ambulance stations; the tenth column indicates the number of helicopter stations, and the eleventh column presents the number of petrol stations.

5.1. Single-objective Results

In this section, results obtained from the solution of random samples are presents. These include the number of ambulances, helicopters, transfer centers and temporary hospitals with various sizes. These are reported in Table 3. It should be noted that since the first objective is the main one in providing relief operations during a disaster, the solution with the lower value for the first objective is considered as the best solution (see Table 3).

According to Table 3, the best solutions for the first and second objective functions can be found among Pareto points. In this table, the values for the first objective function of different problems are almost identical. It is a clear point because it states the maximum time required for leaving the affected areas. The second objective function is obtained in problems with various sizes and large differences because they are very different in terms of fixed costs. Figures 2 and 3 show these differences.

5.2. Pareto Results

This section provides Pareto solutions for different problems. One of the most powerful decision-making tools in multi-objective optimization is the Pareto front as the decision-maker can observe the relationships and trade-offs between all different objectives. These Pareto fronts are given in Figures 4-6.

Table 1
Parameter values

Parameters	Values
t_{ij}	Uniform(1,10)
QA_k	8
QH_h	50
UT_k	5000
DR_i	Uniform(2,5)
DG_i	Uniform(9,15)
ST_i	Uniform(5,10)
$F1_k$	100
$F2_k$	150
E_i	1
L_i	uniform(1000,2000)
HCP_{hi}	1
α	0.8
cx_{ij}	Uniform(10,15)
cy_{ij}	Uniform(30,45)
f_i	10000
$f1_i$	12000

Table 2
Random samples.

Problem	I	K	HC	AA	H	TH	TP	WS	HS	FP
P1	10	2	1	4	1	1	1	1	1	1
P2	25	6	2	12	3	3	2	2	1	2
P3	40	10	4	21	5	3	3	3	2	3

Table 3
Computational results.

Problem	First objective function	Second objective function	Number of employed ambulances	Number of employed helicopters	Number of transfer centers	Number of temporary hospitals
P1	114.113	10081.493	2	1	1	1
P2	135.351	20202.703	6	2	2	3
P3	123.528	30478.420	10	3	4	4
Mean	124.330	20254.205	-	-	-	-

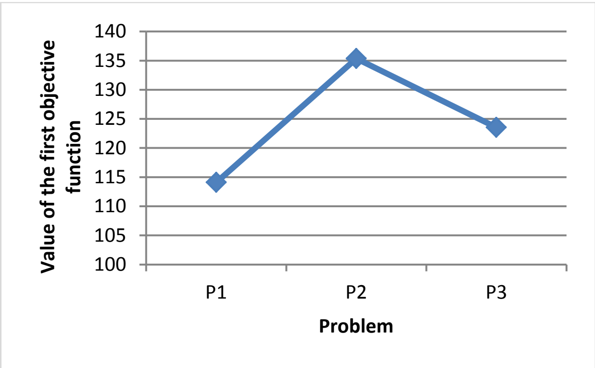

Fig. 2. The first objective function in problems with various sizes.

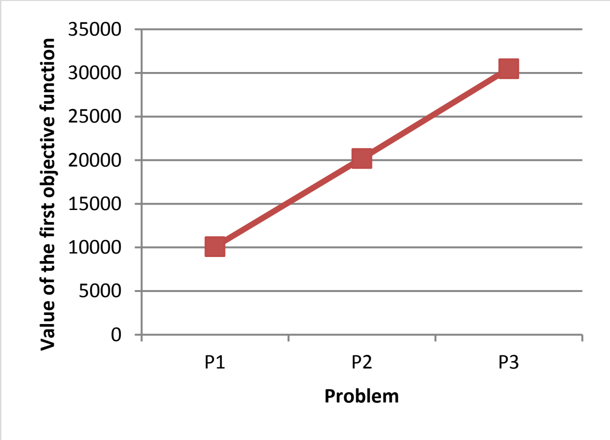

Fig. 3. The second objective function in problems with various sizes.

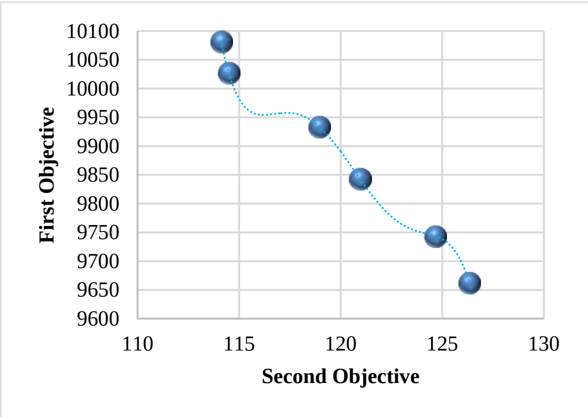

Fig 4. Pareto front of the 1st problem.

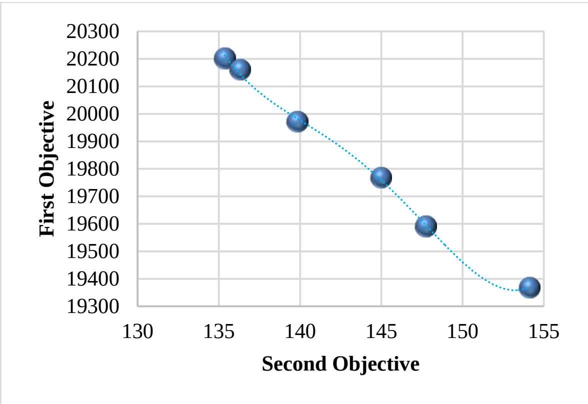

Fig. 5. Pareto front of the 2nd problem.

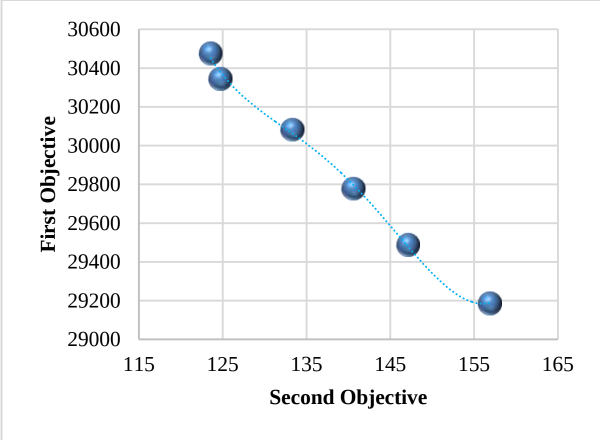

Fig. 6. Pareto front of the 3rd problem.

According to Figures 3-5, different problems have different Pareto fronts with different dispersion degrees. The obtained trade-offs clarify that the objectives are contradictive. In fact, by increasing the value of one of them, the other one decreases. Furthermore, the dispersion of the Pareto fronts in each problem is different.

5.3. Sensitivity Analysis

To investigate the sensitivity of the model to the parameters, a sensitivity analysis is conducted for two key parameters (DR_i and DG_i) of the problem (respectively, the number of injured people in red and green groups). These parameters are demand parameters. These parameters make the problem uncertain (Bozorgi Amiri et al., 2011) and their effects should be analyzed. To this end, the proposed sensitivity analysis is conducted for problem P2, which is a medium-sized problem. The parameters may be changed within a range of %20. Results obtained from the best Pareto points are presented in Tables 4 and 5.

Table 4
Sensitivity analysis for DR_i.

	Obtained results for the changes in the number of injured people (red group) in point *i* of DR_i					
	0.75	0.8	0.9	1	1.1	1.2
Objective function 1	89.201	102.015	116.810	135.351	157.12	183.621
Objective function 2	10772.425	20202.703	20202.703	20202.703	20202.703	20202.703

Table 5
Sensitivity analysis for DG_i.

	Obtained results for the changes in the number of injured people (red group) in point *i* of DR_i					
	0.75	0.8	0.9	1	1.1	1.2
Objective function 1	89.201	102.015	116.810	135.351	157.12	183.621
Objective function 2	10772.425	20202.703	20202.703	20202.703	20202.703	20202.703

In the following, the schematic forms of results are illustrated. In Figure 7, as a result of changes in DR_i, the first objective function is changed. The maximum steep is between %10 and %20. There is a direct relationship between DR_i and objectives.

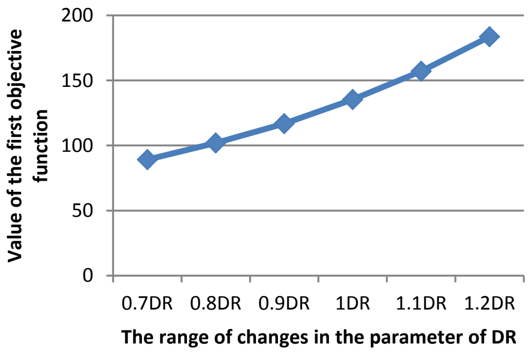

Fig. 7. The first objective function for the changes in DR_i.

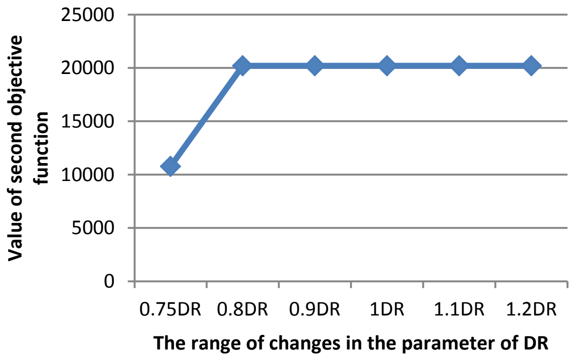

Fig. 8. The second objective function for the changes DR_i.

According to Figure 8, in the second objective function, when DR_i is increased by %20, no changes take place. Also, when this parameter decreased by %20, no changes occur. However, when there is a 25% reduction in the value of DR_i, the second objective experiences a major change.
Regarding the changes in parameter DG_i:

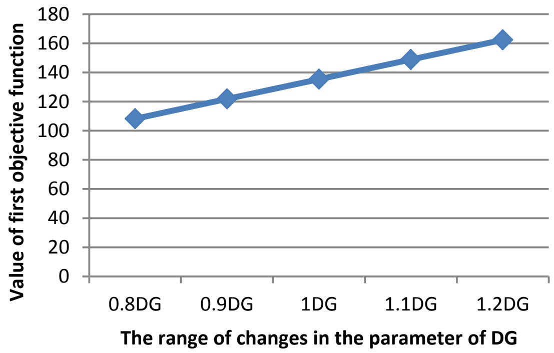

Fig. 9. The first objective function for the changes in DG_i.

According to Figure 9, when DG_i is changed, the first objective function is changed linearly. This shows that there is a direct relationship between this parameter and the first objective function.
In summary, it is concluded that the first objective function is more sensitive to the number of injured people in red group. When the number of the red group increases, the first objective increases with a greater slope rather than the green-labelled injured people. Therefore, this parameter must have a salient role in the process of decision-making at the managerial level.
Managers can determine the optimal values of the objectives by providing the required resources, equipment, and facility for the system limitations, such as the budget constraint. However, the main focus is on the first objective. To this end, an efficient rescue team including relief experts, ambulances, and helicopters can directly affect the value of this objective. Thus, it is suggested that managers consider the results of the sensitivity analysis and provide the required equipment before a disaster occurs.

6. Conclusion

In this paper, relief support planning in urban areas during the disaster was investigated. It was assumed that the degree of severity of injured people is different across the affected areas. The relief system included ambulances and helicopters. In real situations, helicopters had the duty of transporting people with severely injured people. The ambulances were responsible for relieving at the site and transporting the injured people to treatment centers. The study concentrated on planning emergency services through developing a novel bi-objective mathematical model. The objectives were to provide the required services considering the maximum time of leaving the affected area by ambulances and to minimize the network total cost concurrently.

In the first stage, the proper locations of emergency service vehicles and temporary treatment centers were determined. In the second phase, routes for transporting injured people throughout the different points in the network were determined. The purpose was to offer relief services to injured people with different degrees of severity within the shortest possible time considering the limitations and real situations. To verify the efficiency of the proposed model, different-sized problems were investigated and the obtained results were analyzed according to the objective function values, the number of the needed facilities and the trade-offs generated between objectives. As the value of the first objective vitally affects the decision-making, managers can determine its optimal value by providing the required resources, equipment, and facility regarding the system limitations. Eventually, a sensitivity analysis was done for the demand parameter and it was revealed that any changes in the number of injured people may result in different behaviors of objective functions. The changes in both objectives showed their high sensitivity to the red group. Therefore, it can be suggested that the managers need to pay special attention to this issue to reduce the sensitivity by using more equipment.

For future studies, approaches for solving large size samples (e.g., meta-heuristics) can be investigated, like those proposed by Tirkolaee et al. (2018), Goli et al. (2019), and Sangaiah et al. (2019). Moreover, uncertainty approaches such as fuzzy programming (Mostafaeipour et al., 2019) and robust optimization (Golpîra and Tirkolaee, 2019; Tirkolaee et al., 2020) can be employed to make the problem closer to the real world.

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