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Assignment of Injuries and Medical Supplies in Urban Crisis Management

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ABSTRACT

In this paper, we introduce a two stages model for allocation of injuries and medical supplies to medical centers. In the first stage a multi objective mathematical model allocates injured people from the affected neighborhood to medical centers. In the second stage a single objective linear model allocates medical supplies from the supply points to medical centers. The first stage's objective is simultaneously minimizing the total relief time and costs and maximizing the level of matching the type of injury with the specialized field of the medical centers those injuries are sent. The second stage's objective is to minimize the costs of allocating medical supplies to medical centers. An integrated model that combines the two previous models is presented and comparing the results with the two stages model. Proposed models are applied to one of the districts of Tehran to demonstrate their effectiveness. The case study includes two affected neighborhood and four medical centers and three supply points. ϵ-constraint method is used to produce the Pareto optimal solutions in a MOMP.

1. Introduction

Every year, natural or man-made disasters, such as earthquake, flood, drought, hurricane, landslide, volcanic eruption, fire, tsunami, avalanche, extreme cold, heat wave, and cyclone injure thousands of people and destroy worth of habitats and assets [1]. For example one can names the massive earthquakes struck in Kermanshah (Iran) in 2017 and Plasco building fire in Tehran Iran in 2017.

According to a common classification in literature there are four phases in Disaster Operations Management (DOM) as mitigation, preparedness, response and recovery [2, 3].Facility allocation is also another important DOM problem. Although it is mostly a pre-disaster decision, facility allocation requires the consideration of both pre- and post-disaster operations since for an optimal allocation it is necessary to consider the post-disaster activities, such as the distribution of relief supplies [4-9].

Iranian cities, like other cities in the world, are generally exposed to natural or man-made disasters such as earthquakes, floods, fires, terrorist attacks and droughts, etc. There are many factors that make them

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vulnerable to these incidents and the daily lives of many people affected by sudden changes and sees considerable damage. Relief Centers, as the most basic and most important medical institutions, ensure fast and accurate response to the incident. One of the most important strategies to improve the performance of managing the conditions occurred after the crisis is delivering relief supplies as soon as possible to affected people. Also transferring the injured to the relief centers as soon as possible from the scene of the incident play a very important role.

In this paper, we consider urban crisis, such as a fire at a city level such as Tehran. Handling an urban crisis requires different managing tools from the major crises such as earthquakes and floods. In this study, we consider medical items as necessary relief items. A two-stage integer programming model is developed for this problem to minimize the total relief time, the total costs (transportation costs and costs for using therapeutic centers) and maximizing the level of matching the type of injury with the specialized field of the medical centers those injuries are sent. The proposed models allocate medical centers to the affected neighborhoods and also allocate supply points to medical centers in the first and second stages, respectively. The model tackles the emergency condition relief allocation problem as a multi-objective and integer linear programming one. The models are solved by weighting method and ϵ_constraint method.

The rest of this paper is organized as follows: In Section 2, the relevant literature is reviewed. In Section 3, the concept of the ϵ_constraint is described. The general problem description statement is given in Section 4. In Section 5, a solution method is presented. Section 6 reports the numerical results in the case of fire. Our conclusions and future research plans are presented in the final section.

2. Literature Review

An important part of the literature concerned to relief operations management in cities, are about the definition of urban crisis. For example Rumbach, and Follingstad have a study based on MOVE Framework, (a comprehensive framework for assessing disaster and climate risk) in which they find that the urbanization causes rapid spatial growth, dynamic hazard contexts, and limitations in resources and government capacities. The consequences of all of these factors are emerging environmental threats [10]. Lindell, in his handbook emphasizes the intersection of urban planning and hazard mitigation as critical for community resilience, considering the interaction of social, environmental, and physical systems with disasters [11].

Tiernan et al. [12] in their paper reviews the practice and research trends in disaster resilience and risk reduction literature since 2012. The paper uses the rapid appraisal methodology to explore developments in the field and to identify key themes in research and practice. They identify three important emerging themes: socialization of responsibility for resilience; ongoing interest in risk management with an emphasis on public private partnerships as enabling mechanisms; and a nuanced exploration of the concept of adaptive resilience.

Chong et al. [13] proposed a goal programming model to determine humanitarian aid supply and its distribution with uncertainty, regarding the affected population and its resilience. The model considers the efficiency of the logistics system and identifies the level of trust between public, private and academic section.

Kumar et al. [14] proposed a mixed integer model to maximize the demand coverage by including urban space details. They consider the influence of urban settlement elements like built-up compactness in their mode. Liu et al. [15] introduced a bi-objective mathematical model to determine the optimal temporary medical service locations and medical service allocation plan by maximizing the number of expected survivals and minimizing the total operational cost in the way of using ambulances and helicopters.

A key step in emergency rescue, assistance and management is the allocation of emergency resources which includes the provision of relief supplies and affected people [16, 24]. The issue of protecting people's lives, their belongings and urban facilities against natural or man-made hazards is so important that should be considered one of the main objectives of urban planning. In terms of urban planning, urban safety includes all measures and actions which in short-term, medium-term and long-term, maintain human life and property.

Li et al. [17] incorporate demand uncertainty to capture the uncertain nature of disasters. They include financial efficiency and appeal coverage as two key performance indicators to evaluate humanitarian relief chain management, and preform extensive sensitivity and robustness analysis. They analyze the impact of availability of items through distribution centers on relief chain management, and compare the performance of the proposed model under cooperative and non-cooperative scenarios. Zhang et al. [18] presents a multistage assignment model for rescue teams to dynamically respond to the disaster chain and develops three priority scheduling strategies defined under the burden-benefit accord principle. NSGA-II, C-METRIC and fuzzy logic methods were developed to solve the above multi-objective integer nonlinear programming model. Finally, the experimental scenarios results indicate that the overall performance of the proposed method was satisfactory in comparison with current method regardless of whether the secondary disasters occurred sooner or later. Sebatli et al. [19] proposed a simulation _based approach to determine the demands of relief supplies until the governmental and/or central humanitarian organizations (i.e., the Turkish Red Crescent _ TRC) reach to the affected area. They develop a plan to allocate the so-called Temporary-Disaster-Response (TDR) facilities and distribute the relief supplies stored in these facilities. An earthquake case study is constructed for the Yildirim district of Bursa_Turkey including 64 neighborhoods. The relief supplies demands' are determined by analyzing the time it takes for the TRC to reach the affected area using the simulation model with two different system designs. The two_ phase integer programming model is then used to develop a prepositioning plan, i.e., allocation of TDR facilities and distribution of relief supplies. Celik et al. [20] consider the problem of temporary disaster response facility allocation for temporary or short-term disaster relief operations, propose a solution approach and illustrate it with an earthquake case study in Turkey. A two-stage program is developed for the solution of the problem to minimize the total distance traveled, the unmet demands and the total number of facilities (considering the potential difficulties to access the facilities), where facility allocation and service decisions are performed in the first and second stages, respectively. Lutter et al. [21] introduce a robust formulation of the uncertain/probabilistic set covering problem which combines the concepts of robust and probabilistic optimization by introducing Γ _robust α-covering' constraints. This robust uncertain set covering problem can be stated as a compact mixed- integer linear programming model. Additionally, two non-compact integer linear models are developed. Alfredo et al. [22] introduces a very general discrete covering location model that accounts for uncertainty and time-dependent aspects. A MILP formulation is proposed for the problem. In order to tackle large instances of this problem a Lagrangian relaxation based heuristic is developed. A computational study is addressed to check the potentials and limits of the formulation and some variants proposed for the problem, as well as to evaluate the heuristic. Finally, different measures to report the relevance of considering a multi-period setting are studied. Sheu and Pan propose a novel relief supply collaboration approach to address the issue of post-disaster relief supply–demand imbalance in Emergency Logistics (EL) operations [23]. This proposed approach involves two levels of recursive functions: (1) a two-stage relief supplier clustering mechanism for time-varying multi-source relief supplier selection and (2) the use of dynamic programming model to determine a multi-source relief supply that minimizes the impact of relief supply–demand imbalance during EL response. Wang et al. [24] construct a nonlinear integer open location-routing model for relief distribution problem considering travel time, the total cost, and reliability with split delivery. It proposes the non-dominated sorting genetic algorithm and non-dominated sorting differential evolution algorithm to solve the proposed model. Wen et al. [25] within the framework of uncertainty theory, propose an uncertain facility location-allocation model by means of chance-constraints, in which the customers' demand is assumed to be uncertain variables. An equivalent crisp model is obtained via the α-optimistic criterion of the total transportation cost. Besides, a hybrid intelligent algorithm is designed to solve the uncertain facility location-allocation problem, and its viability and effectiveness are illustrated by numerical examples. Barzinpour and Esmaeili [26] propose a new multi-objective mixed-integer linear programming model for preparation planning phase of disaster management. The proposed model is inspired from a real case study of an urban district in Iran, which considers both humanitarian- and cost-based objectives in a goal-programming approach. The location allocation model is solved for both current municipal sub regional zoning and a virtual zoning approach that creates auxiliary cells. Mathematical results show that the second approach can reduce logistic costs and increase total coverage simultaneously. Safaei et al. [27] presented a novel bi-objective bi-level optimization model in order to design an integrated framework for relief logistics operations. The Upper level objectives are to minimize total operational cost and total unsatisfied demand considering the effect of distribution locations of relief supplies. The lower level in the hierarchical decision process, proposes suppliers with lower supply risk. The proposed nonlinear model is reformulated as a single level linear problem, and for the upper-level decision, the goal programming (GP) approach is employed for the exact solution of the model to minimize deviations from the goals of the bi-objective problem. Bozorgi Amiri et al. [28] develop a new approach for modeling a bi objective model for relief distribution system with uncertain demands and supplies, and inaccurate commissioning and transportation costs.

The contributions of the present work are as follows:

- A two-stage mathematical model is developed: In the first stage, the decision is made to send the injuries to medical centers. Secondly, it is decided to send medical supplies from the supply points to the medical centers.
- Maximizing the level of matching the type of injury with the specialized field of the medical centers those injuries are sent.
- Considering a less-extent crisis, such as a fire, in metropolis like Tehran, Iran.

3. Mathematical Modeling

3.1. Problem Description

In this section, we present a two_ stage linear programming model developed for minimizing the total relief time, total costs (such as transportation costs of the injured, The cost of using the medical centers, The cost of sending medical supplies from the supplier to medical centers and the cost of supplier location selection), and increasing the level of matching the type of injury with the specialized field of the medical centers those injuries are sent. Allocation and sending injured people from affected neighborhoods to medical centers is made by the first model. Allocation and sending medical supplies from the supply points to medical centers is made by the second model. Outputs of the first model are the inputs of the second model. The presented third model integrates the two models. The number of injuries is assumed to be uncertain. Fig. 1summerizes the three models.

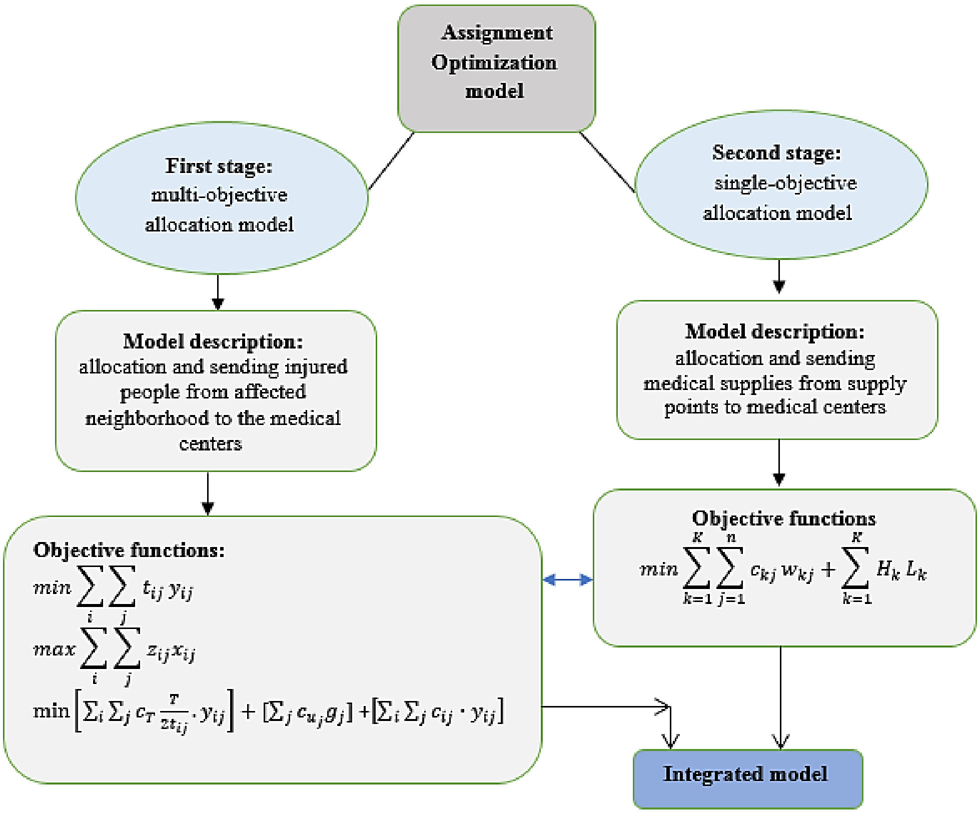

Fig. 1. *Schematics of the problem modeling process.*

The following assumptions are considered in our models:

- Each zone is divided into a number of neighborhoods.
- The center of each neighborhood is considered as the representative point of the crisis.
- The level of matching and type of relief of hospitals and medical centers are different together and are proportion to the type of incident.
- The considered types of crisis are urban crisis.

3.2. First_Stage Assignment Multi Objective Optimization Model

In this section, a mathematical model is proposed to find the optimal assignment of the medical centers to the affected area in order to receive the injured in emergency conditions. The notations are given in the following.

Indices and Sets

i: damaged areas $(i = 1, \dots, I)$.
j: medical centers $(j = 1, \dots, J)$.

Parameters

I: The number of damaged areas.
J: The number of medical centers.
T: Time period (normally 4 hours).
D_i : The number of injured in area i. $(i = 1, \dots, I)$.
t_{ij}: Access time from the area i to medical center j. $(i = 1, \dots, I), (j = 1, \dots, J)$.
c_{ij}: The cost of transferring each injured from area i to medical center j.
C_{Uj}: Cost of using medical center j. $(j = 1, \dots, J)$.
Z_{ij}: Degree of compliance between the types of injury in area i and the expertise field of medical center j. $(i = 1, \dots, I), (j = 1, \dots, J)$.
B_j: The capacity of medical center j to accept injuries. $(j = 1, \dots, J)$.
N_A: The total number of available ambulances.

Decision Variables

$x_{ij} \in \{0, 1\}$ 1 If the area i is assigned to medical center j; 0 otherwise, $(i = 1, \dots, I), (j = 1, \dots, J)$.
$g_j \in \{0, 1\}$ 1 if medical center j is selected; 0 otherwise $(i = 1, \dots, I), (j = 1, \dots, J)$.
y_{ij} The number of injuries transferred from the area i to medical center j $(i = 1, \dots, I), (j = 1, \dots, J)$.

First stage mathematical formulation

Now we present a multi-objective, model by considering the uncertainty in the number of injuries. The model determines the medical centers assigned to the affected areas. The multi-objective assignment model can be written as follows:

$$min \sum_i \sum_j t_{ij}\, y_{ij} \qquad \forall\, i, j \tag{1}$$

$$\max \sum_i \sum_j Z_{ij}\, x_{ij} \qquad \forall\, i, j \tag{2}$$

$$\min \left[\sum_j C_{U_j}\, g_j\right] + \left[\sum_i \sum_j c_{ij} \cdot y_{ij}\right] \tag{3}$$

Subject to:

$$\sum_j x_{ij} \geq 1. \qquad \forall \tag{4}$$

$$\sum_i y_{ij} \leq B_j\,. \qquad \forall\, j \tag{5}$$

$$y_{ij} \leq M \cdot x_{ij}. \quad M >> 0 \qquad \forall\, i, \tag{6}$$

$$x_{ij} \leq y_{ij} \qquad \forall\, i, j \tag{7}$$

$$\sum_j y_{ij} = D_i. \qquad \forall\, i \tag{8}$$

$$\sum_i x_{ij} \leq 2g_j \qquad \forall\, j \tag{9}$$

$$\sum_i \sum_j \frac{N_A}{(I \times J)} \left(\frac{T}{2t_{ij}}\right) \cdot x_{ij} \geq \sum_i D_i \qquad \forall\, i,j \tag{10}$$

$$g_j \epsilon \{0,1\} \;\; x_{ij} \epsilon \{0,1\} \;\; y_{ij} \geq 0 \qquad \forall\, i,j$$

Eqs. (1-3) are the objective functions in the model. Objective function (1) minimize the transportation time of the injured people from the damaged areas to the medical centers. Objective function (2) maximizes the degree of compliance between the injuries and the expertise field of the medical centers. The objective function given in Eq. 3 minimizes the total costs. It includes the transferring cost of the injured and the using cost of medical centers. Constraint (4) ensures that at least one medical center is assigned to any area. Constraint (5) indicates that the number of injured will not exceed the capacity of the medical center j. Constraints (6) and (7) ensure that the injured will be sent only to selected medical centers. Constraint (8) ensures that all the injured in area i will be transferred to medical centers. Constraint (10) restricts the number of transferred injured to the capacity of available ambulances. We assume that each ambulance is assigned only to one direction between an affected area and a medical center. As we have $I \times J$ directions, if all the directions remain active, we will have $I \times J$ ambulances.

3.3 Second_ Stage Assignment Model

In this section, a linear mathematical model is proposed to find the optimal schemes for the assignment of the supply points to medical centers in order to send medical items in emergency conditions. The notations are given in the following.

Indices

k: Supplier $(k = 1, \dots, K)$.
K: The number of suppliers.

Parameters

J' : The set of active medical centers that are selected from the first stage model.
A_j : The demand of medical center *j* for medical item $(j \epsilon J')$.
d_{kj} : Distance from the supplier *k* to medical center *j* $(k = 1, \dots, K), (j \epsilon J')$.
R: Coverage radius.
H_k : The fixed cost of selecting the supplier *k* $(k = 1, \dots, K)$.
C_{kj} : The cost of sending a unit of medical item from supplier *k* to medical center *j* $(k = 1, \dots, K), ((j \epsilon J'))$.
P_k : The capacity of supplier *k* $(k = 1, \dots, K)$.

Decision Variables

$L_k \epsilon \{0,1\}$ 1 if supplier *k* is selected; 0 otherwise $(k = 1, \dots, K)$.

W_{kj} The amount of medical items transferred from supplier *k* to medical center *j*

$(k = 1, \dots, K), (j \epsilon J')$.

The following model determines the supply points allocated to the medical center in order to send the medical items. The model can be written as follows:

$$min \sum_{k=1}^{K} \sum_{j\epsilon J'} C_{kj} W_{kj} + \sum_{k=1}^{K} H_k L_k \quad \forall k \ , \ (j\epsilon J') \tag{11}$$

Subject to:

$$\sum_{k=1}^{K} W_{kj} \geq A_j \qquad (j\epsilon J') \tag{12}$$

$$\sum_{j\epsilon J'} W_{kj} \leq P_k L_k \qquad (j\epsilon J') \tag{13}$$

$$d_{kj} L_k \leq R \qquad \forall k \ , \ (j\epsilon J') \tag{14}$$

$$W_{kj} \geq 0 \ . \ \ L_k \epsilon \{0,1\} \qquad \forall k \quad , \qquad (j\epsilon J') \tag{15}$$

The objective function given in Eq. (11) minimizes the total costs. The costs include the cost of sending medical items from the supplier k to medical center j and the fixed cost of selecting the supplier k. Constraint (12) ensures that the amount of medical items sent from suppliers to medical centers is greater than the demand of the medical centers. Constraint (13) ensures that medical supplies sent from supplier to medical centers do not exceed the capacity of the supplier. Constraint (14) indicates that the supplier distance from the medical center is less than the coverage considered radius.

3.4. Integrated Model

Two separate models presented above, give independently the optimal assignment of injuries to medical centers and the optimal assignment of supply points to medical centers. The reason for this is the independence of the relevant decision centers. But if you set aside this assumption, the two above-mentioned models can be written in the form of an integrated model with the same objectives function and constraints with only one more constraints in order to integrate the two models.

$$\min f1: \sum_{i} \sum_{j} t_{ij}\, y_{ij} \qquad \forall i, j \tag{16}$$

$$\max f2: \sum_{i} \sum_{j} Z_{ij}\, x_{ij} \qquad \forall i, j \tag{17}$$

$$\min f3: \left[\sum_{j} C_{U_j}\, g_j\right] + \left[\sum_{i} \sum_{j} c_{ij} \cdot y_{ij}\right] \quad \forall i, j \tag{18}$$

$$min\, f4: \sum_{k=1}^{k} \sum_{j=1}^{n} C_{kj}\, W_{kj} + \sum_{k=1}^{k} H_k\, L_k \qquad \forall i, j \tag{19}$$

Subject to:

$$\sum_{j} x_{ij} \geq 1 \qquad \forall i \tag{20}$$

$$\sum_{i} y_{ij} \leq B_j \qquad \forall j \tag{21}$$

$$y_{ij} \leq M \cdot x_{ij} \quad M >> 0 \qquad \forall i, j \tag{22}$$

$$x_{ij} \leq y_{ij} \qquad \forall i, \tag{23}$$

$$\sum_{j} y_{ij} = D_i. \qquad \forall i \tag{24}$$

$$\sum_{i} x_{ij} \leq 2 g_j \qquad \forall j \tag{25}$$

$$g_j \epsilon \{0,1\} \qquad x_{ij} \epsilon \{0,1) \qquad y_{ij} \geq 0 \tag{26}$$

$$\sum_{i}\sum_{j}\frac{N_A}{(I\ \times J)}\left(\frac{T}{2t_{ij}}\right)\cdot x_{ij} \geq \sum_{i} D_i \qquad \forall\ i,j \tag{27}$$

$$\sum_{k=1}^{K} W_{kj} \geq A_j \qquad \forall\ j \tag{28}$$

$$\sum_{j=1}^{J} W_{kj} \leq P_k L_k \qquad \forall\ j \tag{29}$$

$$d_{kj}L_k \leq R \qquad \forall\ i,j \tag{30}$$

$$W_{kj} \leq g_j \cdot P_k \qquad \forall\ i,j \tag{31}$$

$$W_{kj} \geq 0 \quad L_k \epsilon \{0,1\} \quad \forall k,j \tag{32}$$

$$g_j \epsilon \{0,1\} \quad x_{ij} \epsilon \{0,1\} \quad y_{ij} \geq 0 \qquad \forall\ i,j \tag{33}$$

Relations (16-20) are defined in the previous section. Constraint (21) indicates that the number of injured will not exceed the capacity of the medical center j. Constraints (22) and (23) ensures that the injured will be sent only to selected medical centers. Constraint (24) ensures that all the injured in area i will be transferred to medical centers. Constraints (25) and (26), by using a zero one variable (g_j), ensure that by selecting a medical center, its fixed cost will be encountered in objective function (18). Constraint (27) restricts the number of transferred injured to the capacity of available ambulances. Constraint (28) ensures that the amount of medical items sent from suppliers to medical centers is greater than the demand of the medical centers. Constraint (29) ensures that medical supplies sent from supplier to medical centers do not exceed the capacity of the supplier. Constraint (30) indicates that the supplier distance from the medical center is less than the coverage considered radius. Constraint (31) ensures that no supplies will be sent to a non-selected medical center.

4. Solution Approach

Multi-objective optimization give a Pareto solution set with many non-dominated solutions, which make it difficult for decision makers to select the final decision from the multiple alternatives available. In the ϵ-constraint method, each time, one of the objective functions is considered as the main objective and the other objective functions are assumed as constraints. To produce a set of Pareto solutions the values of the objective functions in the constraints change between a maximum and minimum range. This change is done by decision maker to produce the desired number of Pareto solutions. Each time, according to one of the objective functions, the problem is solved in the form of a single objective one. Assume the following multi-objective mathematical programming (MOMP) problem:

$$\begin{aligned}&\text{Max} \quad (f_1(x), f_2(x), \cdots. f_p(x))\\ &\text{Subject to:}\\ &X \epsilon S\end{aligned} \tag{31}$$

Where X is the vector of decision variables, $f_1(x).\cdots.f_p(x)$ are the p objective functions and S is the solution space. We use two methods in this paper: weighing sum method and ϵ-constraint method.

4.1. Weighting Sum Method

In this method each objective function is multiplied by its weight, presented by w_i for ith objective function (usually a positive real number between zero and one that whose sum is equal to one). The weighted sum of all objectives is taken as the new objective function for a single objective new problem.

It is proven that by varying the weights of objectives a set of Pareto solutions will be obtained. So the model (31) is transformed to the following:

$$\begin{aligned}&\text{Max} \quad w_1 . f_1(x) + w_2 . f_2(x) + \cdots + w_p . f_p(x)\\&\text{Subject to:}\\&X \in S\\&w_1 + w_2 + \cdots + w_p = 1\\&w_i \geq 0 \quad i=1,\ldots,p\end{aligned} \tag{32}$$

4.2. ϵ -constraint Method

In ϵ -constraint method we optimize one of the objective functions assuming other objective functions as constraints, as shown in the following [29, 30].

$$\begin{aligned}&\text{Max} \quad f_j(x)\\&\text{Subject to:}\\&f_i(x) \geq \epsilon_i \quad i = 1, \ldots, p \quad and \quad j \neq i\\&X \in S.\end{aligned} \tag{33}$$

By parametrical variation of (ϵ_i), and changing each time the objective function, efficient solutions of the problem are obtained. In the literature, several versions of the ϵ -constraint method have been appeared trying to improve its performance or adapt it to a specific type of problems [31, 32]. In this study, we solve the first model using the weighting method, the ϵ-constraint and augmented ϵ-constraint method. We also solve the integrated model by using the ϵ-constraint and augmented ϵ-constraint method.

ϵ_i represents the 'worst' value f_i is allowed to take. It has been shown that if the solution to the ϵ-constraint method is unique then it is efficient [34]. One issue with this approach is that it is necessary to preselect which objective to minimize and the ϵ_i values. This is problematic as for many values of ϵ there will be no feasible solution.

4.3. Augmented ϵ-constraint

Augmented ϵ-constraint improves the conventional ϵ-constraint method for producing the Pareto optimal solutions in multi-objective mathematical programming problems. It is well known that the ϵ-constraint has certain advantages comparing to the weighting method [33]. In this research we use the method introduced by Mavrotas [35]. The steps of the method are as follows.

1) Generate the Payoff matrix.
   1-1) Optimize the first objective function $f_1(x) = f_1*$.
   1-2) Continue to optimize the second objective function $f_2(x) = f_2*$ with the constraint $f_1(x) = f_1*$.
   1-3) Continue to optimize the third objective function $f_3(x) = f_3*$ with the constraint $f_2(x) = f_2*$ and $f_1(x) = f_1*$.
   1-4) Continue the steps above until the payoff matrix is calculated.
2) Determining the value of ϵ.
   2-1) Determine the feasible solution range of each objective function with help of payoff matrix.
   2-2) Divide the feasible solution range into evenly distributed intervals (ϵ).
3) Generate Pareto frontier.

3-1) Optimize the selected objective function with ϵ-constraint and repeat this step to generate the set of Pareto optimal solutions.

3-2) Generate Pareto frontier.

5. Case Study

We implement our approach on a case study for a district of Tehran. In this study, we assume a fire case study shown in Fig. 2. Parastar and Blvd Abouzar are two affected areas from the Piroozi region. The center of each neighborhood is considered as the probable point of the crisis. According to Figs. 2 and 3, we consider three places for supply points, and four medical centers, named $center_1, \cdots, center_4$ (Besat Nahaja General Hospital, Fajr Hospital, Mardom Hospital, Fatemeh Zahra Hospital Corps). Assignment of medical centers to the affected areas and allocating supply points of medical items to medical centers, are shown in Figs. 2 and 3, respectively.

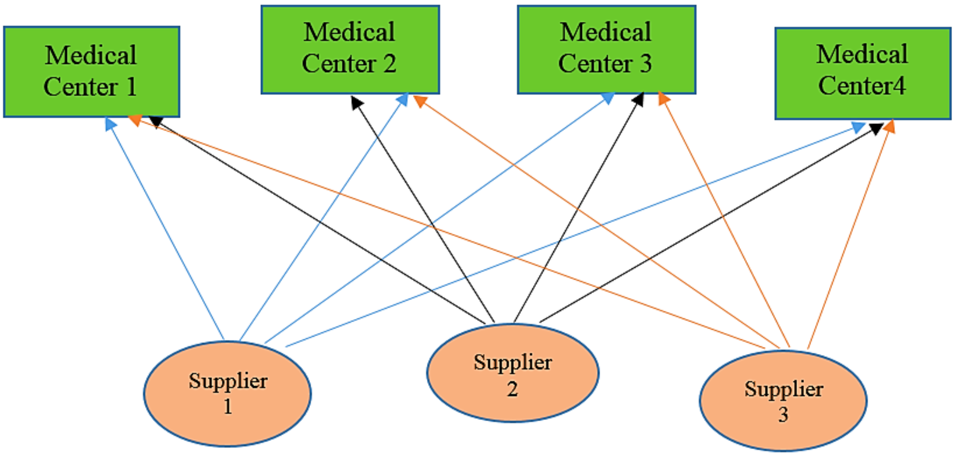

Fig. 2. *Chain structure of the second model.*

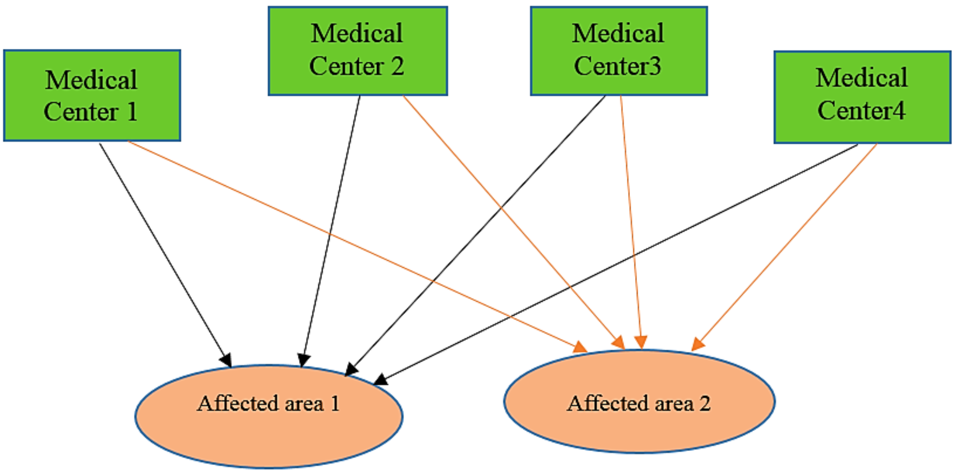

Fig. 3. *Chain structure of the first model.*

Table 5. *Capacities of medical centers.*

Center1	Center2	Center3	Center4
5	15	15	25

Table 6. *Cost of transferring injured people from each area to medical centers (cij).*

i / j	Center1	Center2	Center3	Center4
Area 1	15	10	20	15
Area 2	12	22	16	18

The capacities of each medical center are shown in Table 5. The costs of transferring injured people from each area to medical centers are shown in Table 6. The compliance of matching the injured with the specialized field of medical centers is listed in Table 7. Time of transferring injured people from the affected areas to medical centers is shown in Table 8. The cost of using a medical center is given in Table 9 and the number of the injured people in each area is shown in Table 10. The number of available ambulances is assumed to be 60. The golden total time is assumed to be 4 hours (240 minutes). C_T is assumed to be 11000.

Table 7. *The compliance of matching of medical centers with type of incident (Zij).*

i / j	Center1	Center2	Center3	Center4
Area 1	45%	25%	45%	35%
Area 2	35%	25%	15%	30%

Table 8. *Times of transferring injured people from each area to medical centers (t_{ij}) (minutes).*

i / j	Center1	Center2	Center3	Center4
Area 1	10	15	17	12
Area 2	25	21	23	25

Table 9. *The cost of using medical centers (Cuj).*

medical center	1	2	3	4
The cost of using a medical center	100000	150000	70000	500000

Table 10. *The number of injured in area i (D_i).*

Area1	Area2
30	*20*

The first multi-objective mathematical model is solved by weighting method, ϵ-constraint and augmented ϵ-constraint method. The results are given in Tables (11- 13).

Table 11. *The results obtained from the weighting method.*

w1	w2	w3	f1	f2	f3
0.33	*0.33*	*0.33*	*875*	*175*	*720721*
0.8	*0.1*	*0.1*	*815*	*145*	*720821*
0.7	*0.2*	*0.1*	*822*	*175*	*720812*
0.3	*0.5*	*0.2*	*847*	*175*	*720757*
0.1	*0.8*	*0.1*	*875*	*175*	*720721*
0.8	*0.1*	*0.1*	*815*	*145*	*720821*
0.2	*0.3*	*0.5*	*875*	*175*	*720721*
0.05	*0.9*	*0.05*	*875*	*175*	*720721*
0.03	*0.02*	*0.95*	*875*	*105*	*720705*
0.95	*0.03*	*0.02*	*815*	*145*	*720821*
0.357	*0.285*	*0.357*	*875*	*175*	*720721*
0.1	*0.2*	*0.7*	*882*	*150*	*720712*

The obtained ranges for the best and the worst values of objective functions are as follows:

$$f_1^{Best} = 780$$

$$f_1^{Worst} = 980$$

$$f_2^{Best} = 255$$

$$f_2^{Worst} = 100$$

$$f_3^{Best} = 720705$$

$$f_3^{Worst} = +\infty$$

For using in ϵ-constraint method, the above ranges are divided to equal intervals. Some of the obtained results are presented in Tables 12a, b, and c.

Table 12a. *Some of the Pareto optimal solutions obtained by ϵ-constraint method for time objective function.*

No.	f1	f2	f3
1	*815*	*145*	*720869*
2	*815*	*145*	*720855*
3	*815*	*100*	*720805*
4	*837*	*100*	*720755*
5	*875*	*105*	*720705*

Table 12b. *Some of the Pareto optimal solutions obtained by ϵ-constraint method for quality compliance objective function.*

No.	f1	f2	f3
1	*822*	*175*	*720812*
2	*825.1818*	*175*	*720805*
3	*848.55*	*175*	*720755*
4	*875*	*105*	*720705*
5	*815*	*100*	*720805*
6	*820*	*145*	*720845*

Table 12c. *Some of the Pareto optimal solutions obtained by augmented ϵ-constraint method for cost objective function.*

No.	f1	f2	f3
1	*875*	*105*	*720705*
2	*860*	*130*	*720724*
3	*820*	*100*	*720790*
4	*780*	*120*	*820860*

According to Table 11, due to different weights of objective functions, different optimum points were obtained. Pareto results obtained from the implementation of the model with using the augmented ϵ-constraint method are shown in Tables (12a, b, and c). As can be seen in the above tables the results obtained by augmented ϵ-constraint method are more sensitive and have more variation. On the other hand the ϵ-constraint method provide us better solutions for f1 than the weighting method.

By studying all the above results for Pareto solutions, the decision maker select the following solution for the number of injured that must be transferred from each area to medical centers. As the table below, Area 1 is assigned to medical centers 2, 3, and 4, and area 2 is assigned to medical centers 2, 3 and 4.

Table 13. *The final results selected from the first model for y_{ij}.*

i / j	**Center1**	**Center2**	**Center3**	**Center4**
Area 1	*0*	*5*	*1*	*24*
Area 2	*0*	*10*	*9*	*1*

The data to form the second model from the two-stage model are as the following:

Table 14. *The cost of sending a unit of medical items from the suppliers to medical centers (C_{kj}).*

k / j	**Center1**	**Center2**	**Center3**	**Center4**
Supplier1	*15000*	*20000*	*20000*	*25000*
Supplier2	*10000*	*15000*	*15000*	*20000*
Supplier3	*12000*	*18000*	*20000*	*25000*

Table15. *The capacity of suppliers (P_k).*

Supplier 1	**Supplier 2**	**Supplier 3**
80	*70*	*72*

Table 16. *The fixed cost of selecting the suppliers (H_k).*

Supplier :	**1**	**2**	**3**
Fixed cost	*80000*	*50000*	*60000*

Table 17. *The demand of medical centers for supplies (A_j).*

Medical centers	**Center 1**	**Center 2**	**Center 3**	**Center 4**
Demand for medical supplies	*20*	*15*	*10*	*15*

Table 18. *The distance between suppliers to medical centers Km (d_{kj}).*

	Center 1	Center 2	Center 3	Center 4
Supplier 1	*2.5*	*1.2*	*6*	*2*
Supplier 2	*4.5*	*3*	*4*	*2.1*
Supplier 3	*4.3*	*2*	*1.5*	*5*

The costs of sending a unit of medical items from the supplier to the medical center are shown in Table 14. The capacity of suppliers is shown in Table 15. Table 16 shows the fixed cost of selecting the supplier. The demand of medical centers for medical items is given in Table 17. The distance between suppliers to medical centers is shown in Table 18. We also assume that the radius of coverage is R=5 km. According to the results obtained by the GAMS software, the 1st supplier don't send medical item to medical centers. 2st and 3st suppliers are allocated to all 4 medical centers. So L_1=1, L_2, and L_3=1.

The final results are shown in Table 19. The objective function value is 1000000.

Table 19. *The final results of allocating suppliers to medical centers (w_{ij}).*

	Center 1	Center 2	Center 3	Center 4
Supplier 1	*0*	*0*	*0*	*0*
Supplier 2	*0*	*15*	*15*	*0*
Supplier 3	*20*	*0*	*0*	*0*

In this section, the integrated model derived from the two-stage models is solved using the augmented ϵ -constraint method and some of the results are presented in Table 20.

The obtained ranges for the best and the worst values of objective function f4 are as follows:

$$f_4^{Best} = 1000000$$

$$f_4^{Worst} = 2900000$$

Table 20. *Some Pareto optimal solutions obtained from the implementation of the model with using the augmented ϵ-constraint method.*

No.	f1	f2	f3	f4
1	*815*	*145*	*720869*	*1210000*
2	*875*	*105*	*720705*	*1100000*
3	*815*	*100*	*720805*	*1000000*
4	*825.1818*	*175*	*720805*	*1000000*
5	*848.55*	*175*	*720755*	*2200000*

For example it can be remarked from Fig. 5, the time versus the objective cost f3 has a Pareto nature. As shown in Fig. 4, with lessen the time values, the costs increase and vice versa. Namely, by improving the time, the cost takes worse values.

By comparing the results, it can be seen that the results from the two stages models and the integrated model have not a significant difference.

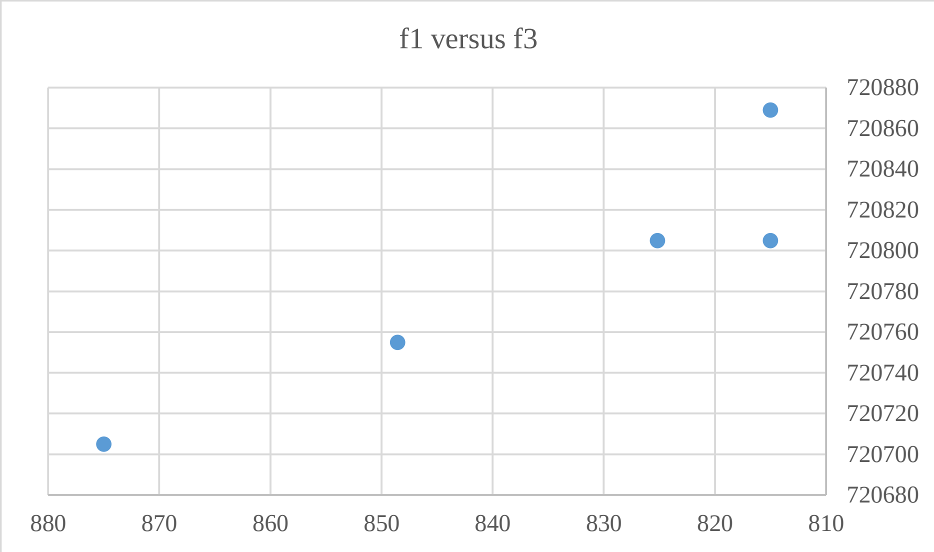

Fig. 4. *The Pareto chart of time objective function relative to cost objective function with using augmented ϵ-constraint method.*

6. Conclusions and Future Works

In this paper, we considered a multi-objective model with considering the uncertainty in the number of injuries in the event of an incident for the assignment and sending injured people from the affected neighborhood to medical centers. A single objective linear mathematical model for the assignment and sending medical items from the suppliers to medical centers in Emergency Condition (EC) is proposed. A fire case study in Iran is used to illustrate our approach. We first develop a two-stage model to minimize the total relief time and total costs and maximizing the compliance of matching the injuries with the specialized field of the medical centers assigned to injuries. The assignment of affected neighborhoods to medical centers and the assignment of suppliers to medical centers for sending the medical items are performed in the first and second stages, respectively. An integrated model that combines the two previous models is then presented. Our case study includes two affected neighborhoods and four medical centers and three medical supplies suppliers. The center of each neighborhood is considered as the probable point of the crisis. Finally, we solve the models by using programming and with weighting, ϵ-constraint and augmented methods. The main contribution of our study is the following: 1. achieving a two-stage model to assign relief facilities 2. Selecting medical items as relief items to handle the situation of the injured. 3. Considering the compliance of matching as one of the objective functions. Our findings show that the integrated model has a better performance in minimizing the total time, but not in maximizing the compliance factor in which the two stages model seems to be better. Also within the solution methods, ϵ-constraint method seems to be better than the weighting method.

As future works, by assuming the demand values to be uncertain, we can develop our uncertain models. Historic data of the number of injuries in different urban crisis around the word can help as to extract the exact distribution functions of demand for different types of disasters. These distribution functions will help us to develop a stochastic two stages and integrated model. In the case of lack of exact data, we can consider the demand uncertainty as a possibilistic distribution and develop the previous models by fuzzy values for demand. By considering the possibilities and medical resources of other districts in our models, we will face large scale models. Developing solution methods for large scale models is another challenge in our future works. Finally considering multi-mode transportation methods for transferring injuries to medical centers, can be another direction in this research.

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