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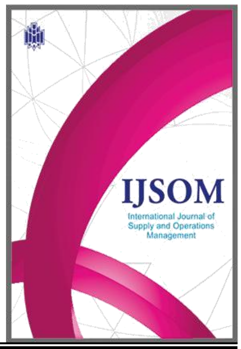

Bi-Objective Model for Ambulance Routing for Disaster Response by Considering Priority of Patients

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Abstract

Disaster situation could suddenly apply large number of injured people and disarrange the emergency medical service simultaneously (EMS). Using all facilities, ambulance, rescue helicopter and medical drone as integrated part and making decision for assigning to patient's efficiency are concerns of EMS. Therefore, in this study we introduce a new bi-objective model for EMS in order to reduce the rate of mobility and mortality with aim of reducing latest service completion time and total cost of system simultaneously. By recognition level of injury, we consider two types of patients: i. red code patients who have been injured seriously and have to be taken to a hospital. And ii. Green code patients who are injured slightly and are treated at the same place. Since making decision and responding to disaster situation should be with high quality within seconds, for this purpose after validating and solving that by augmented ε-constraint method by GAMS, we applied two NSGA-II and customized Bees algorithm for multi objective solution that called Multi Objective Bees Algorithm (MOBA) in dynamics and uncertain situation for coping high frequency within very short response time and near the optimum solution result. The quality of the result is considered for choosing the metaheuristic solution. At the end, sensitive analysis is implemented on the model and the effect of reducing and increasing some of parameters on the model is investigated.

Keywords: Ambulance Routing; Disaster Response; Emergency Medical Service; NSGAII; Multi Objective Bees Algorithm (MOBA).

Motivation

People of each nation are the reason for development of their society. Losing lives causes decreasing the safety level and feeling loss are two bases of each country. Each country invests in their people for their future before they are born and if they lose them, they'll encounter with serious consequences. Furthermore, disaster caused serious damage to infrastructure of nations and they could not prevent from happening and foreseeing it, but they could prevent from serious consequences. Hence, learning from previous similar situation and mobilizing their responding systems is important. Therefore, emergency medical services defined for this purpose. Performance evaluation and preparation of EMS are so substantial. As this situation has serious uncertainty, vague, large patients and large damage, EMS should respond super efficiently. Accordingly, the aim of this study is to evaluate the EMS and propose the solution for decreasing morbidity and mortality. Since routs maybe block and most patients are seriously injured which lead to increase the costs and waste the time, therefore, considering vehicle routing problem could minimize vehicle routing times and latest service completion time effectively. Hence, giving priority to them and considering different vehicles like rescue helicopters and ambulances could lower the rate of morbidity and mortality.

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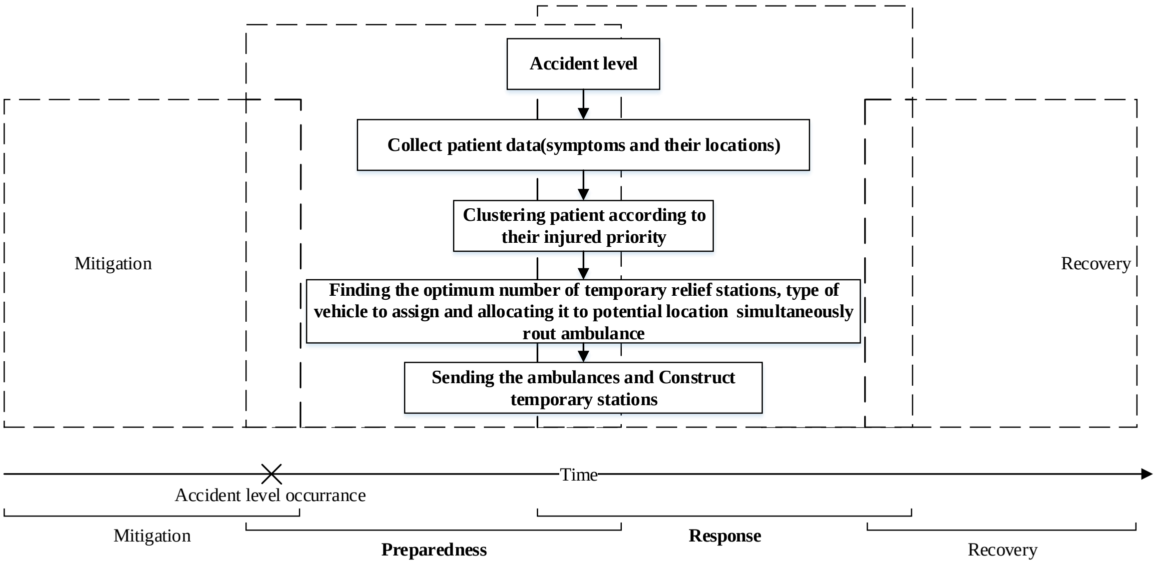
1. Introduction

Natural

Disaster causes damage to infrastructures, financial losses and loss lives in each country every year. Iran was placed among the top disaster-prone countries in the world (Guha et al., 2004). Recent examples such as 2017 Northwest floods in Iran, Bushehr tsunami in 2017, Murmuri earthquake in 2014, Tehran heavy storm in 2014 and man-made disaster called Iran- Iraq war in 1988. Throughout recent decades, the increase in population has made capital cities into densly-crowded ones. Also, old constructional buildings and old building structures has increased the risk of other crises.

Normal infrastructures and EMS system could not respond in disaster. Disaster occurs out of blue it's time of occurrence, type of disaster and Depth of the crisis are not predictable. Last disaster taught us that we should be ready for these situations (Caunhye et al., 2012). (Eshghi & Larson, 2008) presented the crisis categories in three levels: (1) Emergency: an event occurring locally to people high on the priority for response and by normal EMS system could respond. Usually patients who have short period of time to lose their life is an Emergency situation. Predicting the patients' demands and assessing the EMS system are considered as two concerns in this field. The models that are written in this field should be dynamic which could accept new patient in each time (Ghiani rt al., 2003). (2) Disaster: a sudden event with large number of patients with critical injuries. EMS system could not respond exactly to patients and needs cooperation of another EMS organization widely (Seidgar et al., 2016). The infrastructures may damage. Some of local EMS system may go off the service or blocked. In this field, the first priority is to reduce the rate of mortality and morbidity. Earthquake and war are common disasters in world. (3) Catastrophe: the event with large damage which local EMS system will be destroyed, most of people will be killed and are destroyed most of the commodities. This event overshadows whole world. To find out the level of crisis, there are many other items and events which could be placed amid these levels. In each level, it is very important to reduce response time to critical injured people to save their lives. This process reduces rate of morbidity and mortality. For example, if you are in emergency situation and have two patients one of them been has seriously damaged or is having his/her last breaths, it is important at first serve him/her and if normal ambulance could not save his/her life we should assign more expensive vehicles like rescue helicopter or one that could save that patient. It is also noteworthy that the life of each patient is more significant than each EMS serving system. Although EMS tries to cut down the expenses. This study could be assessing and responding each levels of accidents. Although the main focus of this study is the levels between Catastrophe and disaster.

Management of Each one of these accident levels are categorized in four phases for studding, assessing and responding: (1) Mitigation, (2) preparedness, (3) response and (4) recovery as shown in Figure 1. These four phases cover whole actions of EMS (Altay & Green, 2006). Mitigation is set of applications to predict and prevent the start of accident levels like disaster. It measures probability of accidents levels and tries to present set of solutions for activation to reduce the onset or reduce consequences. It is important phase with base of researches approach, investigating this phase reduce elimination of infrastructure, costs of other phases and rate of morbidity/ mortality (Scholten et al., 2014). Resilience approach is new attractive research in this phase (Paton & Johnston, 2017). Preparedness is set of activities with base of mitigation to prepare for accident level and reducing consequence of accident levels. This phase is placed in pre-accident level for preposing equipment of relief inventories (Kunz et al., 2013). Some relief equipments are deteriorating, their logistics are very important and replacing them at the right time is of high sensitivity (Birnbaum et al., 2016). Response is set of activities; traumatic accident level for assigning EMS, relief equipments for responding to patients. It is actual an activity in post-accident level, reducing response time, reducing rate of mortality and morbidity, patient satisfaction and reducing costs are important issues in this phase (Van et al., 2014). Recovery is section of post disaster for distribution of emergency goods to the people being affected by accident levels. It is placed in logistic humanitarian aids, the first aid like water, food, first aids are in this phase (Tirado et al., 2012). Evacuation affects people and making shelter for them are critical activities for post-disaster or post-catastrophe (Yi & Özdamar, 2007). This was the first study by simulation of prone disaster as earthquake in Tehran, the capital of Iran, proposed solutions to mitigation and preparedness phases by finding the errors of EMS and shortage of equipments. And also, this model could apply for response phase and recovery phase. By giving the data of patients and situations of accident level. As this problem in big size placed in np-hard problems for this purpose presented metaheuristic solution of NSGA-II and MOBA for reducing response time of problem. Bees algorithm customized and this study proposed multi objective bees' algorithm (MOBA) at the first time.



Flowchart of process

Figure 1. The phases of accident levels and

As it is shown in Figure 1, the response process should be designed efficiently. These problems in disaster and catastrophe levels will be determined with Shortage of equipments, problem is dynamic and as some patients have been seriously injured, it could not treat them in a very short time, they lose them. Hence, EMS should decide quickly for the response. Also, we figured with scarce ambulances and other EMS vehicles. Routing problem of EMS vehicles in different situations can be solved statically or dynamically (Aringhieri et al., 2017). In emergency level, we face discrete patient request, in disaster and catastrophe level EMS is faced with large number of patients at the same time, hence this study is considered as static case. The process was executed by central EMS system for the dispatch. First EMS identified accident level. Then by collecting incoming request for treatment. It collects location of each patient, their symptoms and their condition. The EMS dispatchers several treatment request and clustering them by symptoms and EMS severity anticipation in second step. The clustering shows patients on the priority to respond speaking of critical time for lives of patients which is used for vehicles dispatching and sort of services. This analysis before sending EMS vehicles, increasing efficiency of EMS system. Hence unlike the previous models which were used in past research, at the first, this model responds to urgent patients and reduce morbidity/mortality rate. Some urgent patients may be far from EMS location or rout may block by casualties. Hence for saving their life EMS assigned other vehicles type like rescue helicopter which has different respond time and costs. To saving life of patients are more important than costs so model result shows different optimum solution with different assigning type for better decision on EMS center. In other word, if EMS predicts it can be served by cheaper vehicles and they survived, it accepts to assign. The new request may come so model can repeat from collecting patient data at high frequency. So, this model for accident and catastrophe level is mixed of static and dynamic response process. By repeating this sketched plan, you can find out more benefit details like infrastructure condition, availability of EMS vehicles and etc.

The main focus of this study is on investigating the problems by different types of vehicles which is placed in respond process. Although by simulation this process could present solutions for phase of accident levels. The EMS vehicles are used for serving patients in place and for high injured people, carrying them to the hospital. According to the priority, patients distinguish in two types:

- **Critical-Patient**: patients with Critical injuries which need quick respond from EMS to save them. They must be taken to emergency centers or hospital (Red patient).
- **Normal-Patient**: slightly injured patients who could even walk to EMS centers or hospitals and EMS treat them on their positions (Green patient).

High emergency patient will be dead if They don’t treat him/her immediately. They have high priority to respond to prevent from losing them and decries mortality and morbidity. An intelligent algorithm developed to recognize patient situation with their symptoms. See e.g., (Lerner et al., 2011; Travers et al., 2002 & Kahn et al., 2009).

This study is based on mitigation phase and by simulating different accident levels, patients’ size, prone location and different relief inventories proposed solutions. Also, the model could apply for accident level respond phase to find out near optimum solutions in short time. The main accident level which is focused is disaster situation. EMS faced with large

number of patients and scarce equipments like first aids, etc, the main thing is scarce is studying in vehicles for treatment. Hence, we consider different EMS vehicles like rescue helicopter and ambulances for treatment.
The rest of paper, reviewed last studies in this field and related them to this study in Section 2. In Section 3 presented the model and problem description. In Section 4 we present solution approach, augmented ε-constraint, NSGA-II and new metaheuristic solution for multi objective problems called Multi Objective Bees Algorithm (MOBA). The validation and verification are tasted in Section 5. In Section 6 presented conclusion and future work suggestion.

2. Literature review

(Fitzsimmons et al., 1982) Studied permanent situation for calling emergency ambulance in Austin, Texas. to enhance the availability of optimization, it used contiguous zone search routing (CZSR) and coupled it with an existing emergency simulation. Emergency calls to improve the average response time systematically. With regression model in normal situation, demand for emergency developed and showed the variables in demographic data are independent. This study proposed GIS map for idle time for patient service in Austin and funded out the potential candidates for EMS vehicle system holding. (Goldberg & Listowsky, 1994) Presented different dispatching field and find out the critical factor to determine expert system and introduced Road utilization learning expert systems (RULES). (Goldberg et al., 1990) Introduced simulation model for evaluating Emergency response by their vehicle locations. In their article, it was mentioned that there is an increasing density of population in each city which reflects it in EMS that became more challengeable and difficult. Also, travel time, time in scene, time in transporting to hospital and time at the hospital are the factors that are calculated exclusively. It also mentioned service time of each victim is related to their locations. They assumed that travel time in different demand and locations are different. Paramedic method and finding the priority of patients presented by (Garner et al., 2001) Triage sieved patient has different priority for dispatching the facilities with considering vital sign, walking, could breathing, limitation of respiratory rate and capillary refill to stratify patients. And they compared it with the method of North America widely. In their study, Sequence of paramedic rule is: ability to obey commands, respiratory rate, and capillary refill to assign. Identifying the physiologic or anatomic sign of severe injury and high-risk mechanism of injury to transpose the patient are very crucial to assign the best dispatching method of ambulance. In trauma, centers care about the time of Hospitalization unit, patient transportation and the age of patient. (Brotcorne et al., 2003) Traced evolution of assigning ambulance location and relocation until 2003 (review paper models). In their article, the past studies are divided into two categories, deterministic models with considering the availability of ambulances and probabilistic models regarding queuing and unavailability to respond calls. (Altay & Green, 2006) described that disaster impacts on problems which are under influence of infrastructure and populations in dynamic demand situation in aspect of matter real-time and effective respond to incidents.

As Emergency response in disaster events is not like daily response of ambulance, police, or fire station in routine response, Federal Emergency Management Agency was established in 1977. And studies in emergency situations started over there and in university level started in the mid of 1980s, in United States with relativity of low priority for the problems. (Tufekci & Wallace, 1998) Suggested clustering response efforts in two stages; prevent and post-event. (Green, 2002) mitigation, preparedness, response, and recovery are four phases of emergency response. (Andersson & Värbrand, 2006) showed medical treatment of patients and transportation of patient are important factors in ambulance logistic. Also, they said that waiting period as a time between calling patient after incident until ambulance gets to patient. It is commonly called response time and it tries reducing this time by finding optimal locations for ambulance stations. They used simulation model for their proposed model. The problems exposed dispatching and relocating of them by some time period. Patients are considered as three different priorities 1) most urgent (life-threatening), 2) urgent but not life-threating, and 3) non-urgent. (Yi & Özdamar, 2007) used an integrated model in order to find optimal location for centers and shelters in disaster response by maximizing the medical coverage and considering distance of these with hospitals in Istanbul. They assumed that demands in disaster response might be greater than anticipated, and obviously transportation has delay. In their study open VRP means are used, the vehicle won't need to come back to center. (Campbell et al., 2008) considered node for each customer with re arranging their location and designated depot. Then minimized arrival time to customers and for each costumer and considered windows limiting delivery time. This paper Compound TSP and VRP and used objective as, minimax and minsum. minimax, minimized the maximum travel time and minsum minimized total travelled time. It compared TSP with VRP actually. (Rajagopalan et al., 2008) studied determined minimizing the number of ambulances and locating. By relocation and redeployment of ambulance response enhanced reliability of result. (Zografos and Androutsopoulos, 2008) modelled implementation of hazardous VRP in Greece. (Iannoni et al., 2009) located ambulance station in highways. (Jotshi et al., 2009) disaster-earthquake scenario-simulation. (Kahn et al., 2009) disaster-train crash in 2003 clustered injured people in three section red, yellow and green patients. (Tatham and Kovács, 2010) introduced application became more trust to the answers and trusting. (Berkoune et al., 2012) it considered to minimize the duration on transportation of goods in disaster situation and solved in whit GA. (Caunhye et al., 2015) gathered the key challenge of disaster situation. (Torre et al., 2012) keywords "disaster", "emergency", "catastrophe", "humanitarian" mention.

Table 1. literature review table

Authors	Integration	simulation	Multi-objective	Meta heuristic	Different type of vehicles	Patient priority	Ambulance routing
(Vahdani, Shekari, & Mousavi, 2016)[	✓	✓	-	✓	-	-	✓
(Saeidian, Mesgari, & Ghodousi, 2016)	✓	✓	-	✓	-	-	✓
(Tavakkoli-Moghaddam, Shishegar, Siadat, & Mohammadi, 2016)	-	✓	✓	✓	-	-	✓
(Aringhieri et al., 2017)	✓	-	✓	-	✓	✓	✓
(Berkoune et al., 2012)	-	✓	-	✓	-	-	✓
(de la Torre et al., 2012)	✓	-	-	-	✓	✓	✓
(Caunhye, Nie, & Pokharel, 2012b	✓	-	-	-	✓	✓	✓
(Jaldell, Lebnak, & Amornpetchsathaporn, 2014)	-	✓	-	-	✓	-	✓
(Silva, 2016)	-	✓	-	-	-	-	✓
(Abounacer, Rekik, & Renaud, 2014)	-	✓	✓	✓	-	-	✓
(Talarico, Meisel, & Sörensen, 2015)	✓	✓	-	✓	-	✓	✓
(Yi & Özdamar, 2007)	✓	✓	-	-	-	-	✓
(Kahn et al., 2009)	✓	✓	-	-	-	✓	-
This study	✓	✓	✓	✓	✓	✓	✓

3. Problem Description

The main purpose of the proposed problem is ambulance routing to assist and serve patients in the event of a natural disasters, so that be at least the time and cost of service to patients. The notations used in this article are listed in Table 2. In this article the patients are divided into two groups: 1) red code patients and 2) green code patients. Red code patients for service are taken to the hospital h by ambulance, but green code patients are not taken to hospital and are treated at the same place.

3.1. Mathematical Model

In this article we are dealing with two types of ambulance (A typical ambulance and rescue helicopter). If we use a conventional ambulance, we will have high -time service and low-service costs and if we use the rescue helicopter, we will have low -time service and high -service cost. So, in this article we look forward to serving the patients to determine a path for ambulances to depend on type of ambulance the time and cost of services to patients are minimized. Shown capacity hospital *h*, that). We have assumed that each ambulance has the ability to transfer a red code patient to the hospital and also, we have assumed that each ambulance after reaching to patients goes to hospital. The mathematical model for this problem is as follows:

Table 2. Notation used to model the ambulance routing problem.

Sets:	
R	set of red code patients
G	set of green code patients
P	set of all patients,
H	set of hospitals
K_W	set of type ambulances w that are initially located at hospital w=1,2
K	set of all ambulances
j	set of all patients and hospitals
i	set of green code patients and hospitals
Parameters:	
f_{hk}	binary parameter 1 if ambulance k is initially located at hospital h
t_{ip}	travel time from i to p
t_{rhk}	travel time from r to h with ambulance k
c_{jmk}	cost from j to m with ambulance k
d_j	service time of patient j
c_h	capacity of hospital h
c_{pk}	service cost of patient p with ambulance k
d_h	transfer time to drop off a red code patient at hospital h
w_r	priority given to red code patients
w_g	priority given to green code patients
Decision variables:	
x_{jmk}	binary, 1 if ambulance k serves patient j directly before patient m
b_j	visiting time of patient j
E_r	latest service completion time among all red code patients
E_g	latest service completion time among all green code patients

$$\text{Min } Z_1 = w_g.E_g + w_r.E_r \tag{1}$$

$$\text{Min } Z_2 = \sum_j \sum_m \sum_k x_{jmk}\, c_{jmk} + \sum_p \sum_j \sum_k x_{pjk}\, c_{pk} \tag{2}$$

S.t.

$$\sum_p x_{hpk} \le f_{hk} \qquad \forall\, h,k \tag{3}$$

$$\sum_k \sum_j x_{jpk} = 1 \qquad \forall p \tag{4}$$

$$x_{hgk} + x_{ghk} \le 1 \qquad \forall\, h,g,k \tag{5}$$

$$\sum_j x_{jpk} = \sum_j x_{pjk} \qquad \forall\, \text{p, k} \tag{6}$$

$$\sum_h \sum_k x_{rhk} = 1 \qquad \forall\, r \tag{7}$$

$$\sum_{r}\sum_{k} x_{rhk} \leq c_h \qquad \forall\, h \qquad (8)$$

$$b_i + d_i + t_{ip} \leq b_p + \left(1 - \sum_{k} x_{jpk}\right).M \qquad \forall\, i,p \qquad (9)$$

$$b_r + d_r + t_{rhk} + d_h + t_{hp} \leq b_p + \left(2 - x_{rhk} + x_{hpk}\right).M \qquad \forall\, r,p,h,k \qquad (10)$$

$$Eg \geq b_g + d_g \qquad \forall\, g \qquad (11)$$

$$Er \geq b_r + d_r + d_h + (\sum_{k} x_{rhk} t_{rhk}) \qquad \forall\, r,h \qquad (12)$$

The first objective function minimizes the service completion time of red code patients and green code patients. The second objective function minimizes the cost of the using of ambulance type k and the cost of a service to patients. Constraint (3) guarantee that any ambulance that is at first in a hospital, can be served to the patients. Constraints (4) and (5) ensure that each ambulance will visit exactly one of the patients. Constraint (6) guarantee that when there are no patients left unvisited the ambulances final destination will be one of the hospitals. Constraint (7) means that the red code patients should be delivered to hospital and Constraint (8) tells that the number of patients whom will be transported to each hospital should not exceed the capacity of that hospital. Constraints (9) and (10) show the time that each ambulance will visit a patient at his/her location. Constraints (11) and (12) determine the time in which the service to each red code patient and green code patient is over.

3.2. Illustrative Example

In this section, we examine a small problem and compare the solutions obtained from the NSGA-II and MOBA algorithms with the solution GAMS. In this example, there are three red code patients; $R = \{R_1, R_2, R_3\}$ and seven green code patients; $G = \{G_1, G_2, \dots, G_7\}$. The number of hospitals are two; $H = \{H_1, H_2\}$ and the capacity of each of the hospitals is two. (in hospital H_1 three ambulances are located and two ambulances are located at hospital H_2). We consider two types of ambulances: regular and rescue helicopter. The cost of using a regular ambulance is 5 monetary unit and rescue helicopters are 10 monetary unit (. Figure 2 shows the locations of hospitals and all patients.

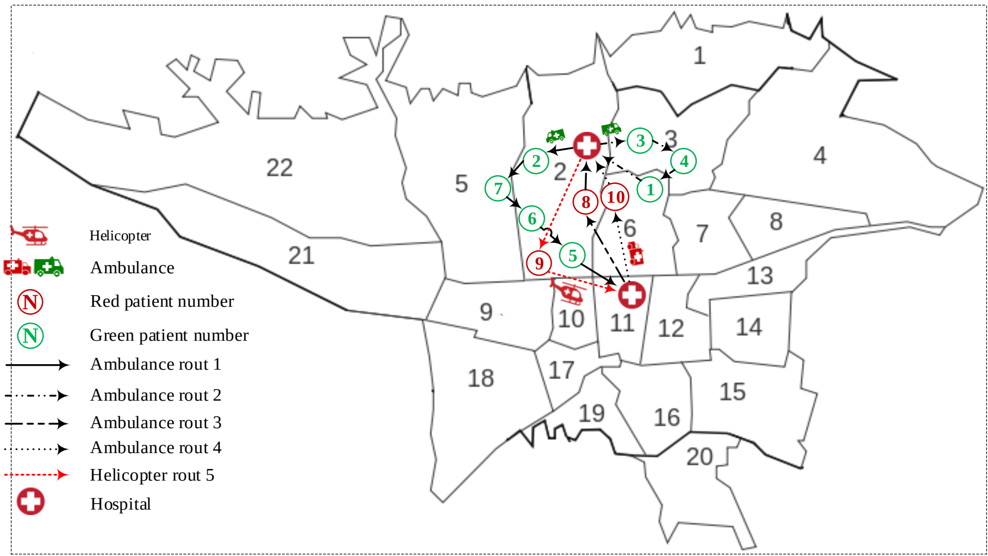


Figure 2. EMS Routs map in Tehran, the capital of Iran

4. Methodology

In this study we used *augmented ε-constraint* to solve exactly model. And for large size used NSGA-II and MOBA. The rest of this section we present these methods.

4.1. Augmented ε-Constraint

There are several common methods to solve multi-objective like minimax, weighted sum, ε-constraint and metaheuristics. (Mavrotas, 2009) introduced augmented ε-constraint method and developed it (Mavrotas & Florios, 2013). (Balaman, 2016) showed the advantage of ε-constraint methods. To solve the multi-objective problem with augmented ε-constraint method that can be written as follows:

$$Max(\gamma + \varepsilon \times \sum_{\partial \neq \gamma} ({}^{S_\partial}/_{R_\partial})) \quad (13)$$

$$\partial - S_\partial = L_\partial, S_\partial \geq 0, \partial \neq \gamma \quad (14)$$

4.2. Solution Representation

How to produce initial number is so important and getting results consequence. Hence to make significant quality number has an effect on computational time and quality of solutions at the end. For producing initial structure in both metaheuristic bellow approach is used string number between 0 and 1 which is called them chromosome? The first string is created by $P+A-1$ with random generation numbers. P is the number of patient input and A is the number of different EMS vehicles (ambulance, rescue helicopter). The result of this work is to produce random permutation.

The permutation specifies the assignment of patients to the available EMS vehicles. The numbers between 1 to P presents patients and bigger than the number of P present type of EMS vehicles. The numbers in between [$P+1$, $P+A-1$] have buffer rules for recognizing which patients are assigned in which EMS vehicles. Patient in first buffer are assigned to the first ambulance. Patients between first buffer and the second buffer are assigned to the second ambulance. If there weren't other numbers between two buffers, it would mean no patients are assigned to the ambulance. Figure 3 is shows a permutation example of assignment patients to EMS vehicles. Number 12, 11, 14 and 13 presented the buffers. Also, ambulance 1 is assigned to patient 3, ambulance 2 is not assigned to patients, ambulance 3 is assigned to patients 9, 5,10,4 and 7, ambulance 4 is assigned to patients 6,1 and 2. And rescue helicopter 1 is assigned to patient 9. Patients' number 1 to 7 are green code patient and 8 to 10 are red cod patients.

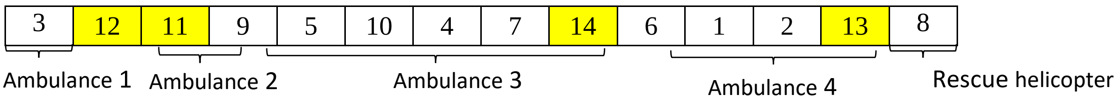


Figure 3. Permutation, Ambulance assignment to patients

4.3. NSGA-II

One of the Most Common conventional methods to solve multi-objective problems is NSGA-II. (Deb, et al., 2002) Extended the NSGA and introduced NSGA-II. The flowchart and Pseudo code of NSGA-II are shown in Figure 4 and Figure 5.

4.4. Multi Objective Bees Algorithm

Bees algorithm is one of the well-known population-based algorithms that developed by (Pham et al., 2011). Our proposed
s combined with NSGA-II operators. The crowding distance
plied to improve the implement of classic BA. The steps of

1. *Generate initial random feasible result for populations.*
2. *calculate objective functions.*

   For(x=1 to max Iteration) do

3. *Select populations randomly.*
4. *Apply crossover to create new Childs.*
5. *evaluate objective functions.*

   Repeat 3-5 to create children

6. *pickup results randomly as a parent and apply mutation function*
7. *evaluate it*

   Repeat 6 and 8 to create members with mutated population

8. *Merge results*

   For(j=1 to last members)do

9. *Assign crowded distance*
10. *Ranked by fast non-dominated-sorting*
11. *insert to Pareto front*

    End

12. *Select members according to rank and diversity*

    End

ctive functions.
ites and evaluate objective functions, crowding
dance
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lominated sorting insert to Pareto front
aluate objective functions, crowding distance and
owding distance in Pareto fronts

A Pseudo code

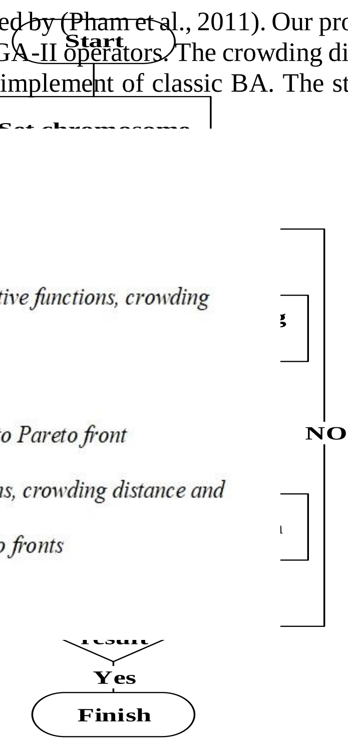

Figure 4: NSGA-II Pseudo code

Figure 5: NSGA-II flowchart

In this section we are changing the parameters such as hospitals, ambulances, type of ambulances green code patients and red code patients, different issues have been created in small sizes and large sizes so we can compare NSGA-II algorithm and MOBA algorithm. The results of comparisons of NSGA-II and MOBA algorithms are shown in Tables 3 to 10. Problem characters in Tables 3 to 10 are in order of the number of hospitals, ambulances, type of ambulances green code patients and red code patients. To compare the efficiency of the two NSGA-II and MOBA algorithms, four comparison metrics such as spacing metrics (SM), mean square index (MSI), mean ideal distance (MID) and number of Pareto solutions were used. This type of metric allows us to compare the uniformity of the distribution of the solution obtained by each of the algorithms. The results of SM calculations are presented in Tables 3 and 4. This metric is computed as follows:

$$SM = \sqrt{\frac{1}{N-1} \times \sum_{i=1}^{n} (d_i - \bar{d})^2} \tag{15}$$

d_i : The Euclidean distance between solution *i* and the nearest solution belonged to Pareto
: The average value of all d_i

MID matric shows the total distance between the obtained answers and the ideal answer for each of the objective functions. The results of MID metric are presented in Tables 5 and 6. Since all our objective functions are minimized, then the ideal answer in this problem is considered as the point of (0, 0).

f_1^i: The answers obtained from the first objective function, where *i* is the number of Pareto

f_1^{best}:Ideal answer for first objective function

$f_{1,total}^{min}$:Minimum value of the first objective function

$f_{1,total}^{max}$: Maximum value of the first objective function

MID metric is computed as follows:

$$MID = \frac{\sum_{i=1}^{N} \sqrt{\left(\frac{f_1^i - f_1^{best}}{f_{1,total}^{max} - f_{1,total}^{min}}\right)^2 + \left(\frac{f_2^i - f_2^{best}}{f_{2,total}^{max} - f_{2,total}^{min}}\right)^2}}{n} \tag{16}$$

MSI is the main square of the maximum value of objective function minus the minimum value of the objective function. The results of MSI metric are presented in Tables 7 and 8. The number of Pareto solutions shows the ability of the algorithm to find the effective point and the computational time and the results are presented in Tables 9 and 10.

Table 3. SM for small size

Average	**0.237056**	**0.083864**
Problem characters (R-G-H-K-K_2)	NSGA-II	MOBA
3-7-2-5-1	0.4	0
4-7-2-5-1	0.4	0
4-9-2-6-2	0	0.832091
4-9-2-7-2	0	0.539882
5-12-3-7-2	0.053873	0.166666
9-15-3-7-2	0.399657	0
9-18-3-7-3	0.344339	0
11-20-3-7-3	0	0
15-30-3-7-3	1.172687	0
15-30-3-10-3	0	0

Table 4. SM for large size

Average	**0.983484**	**0.529952**
Problem characters (R-G-H-K-K_2)	NSGA-II	MOBA
15-35-3-10-3	0	0.263636
16-36-3-10-3	0	0
16-40-3-12-3	0.399533	0.587523
17-45-3-12-3	0.398589	0.783720
18-45-3-12-3	0	0.889247

18-50-3-13-3	0.299887	1.220754
20-60-3-14-4	0.399995	0
25-75-4-15-4	7.837356	1.021951
30-90-4-15-4	0.328154	0.832707
35-100-4-18-5	0.471371	0

Table 5. MID for small size

Average	**0.881219**	**0.884215**
Problem characters (R-G-H-K-K_2)	NSGA-II	MOBA
3-7-2-5-1	0.900223	0.813784
4-7-2-5-1	0.876587	0.889447
4-9-2-6-2	0.859888	0.906339
4-9-2-7-2	0.881531	0.916663
5-12-3-7-2	0.902762	0.904723
9-15-3-7-2	0.907753	0.912304
9-18-3-7-3	0.900707	0.889304
11-20-3-7-3	0.873995	0.903686
15-30-3-7-3	0.896344	0.805538
15-30-3-10-3	0.812394	0.900356

Table 6. MID for large size

Average	**0.898784**	**0.898749**
Problem characters (R-G-H-K-K_2)	NSGA-II	MOBA
15-35-3-10-3	0.896581	0.901359
16-36-3-10-3	0.890963	0.881656
16-40-3-12-3	0.897367	0.901005
17-45-3-12-3	0.899695	0.901499
18-45-3-12-3	0.893216	0.900883
18-50-3-13-3	0.902307	0.900353
20-60-3-14-4	0.901192	0.899728
25-75-4-15-4	0.903963	0.900817
30-90-4-15-4	0.901998	0.900393
35-100-4-18-5	0.900549	0.899788

Table 7. MSI for small size

Average	**0.01849**	**0.051832**
Problem characters (R-G-H-K-K_2)	NSGA-II	MOBA
3-7-2-5-1	1.100223	0.088765
4-7-2-5-1	1794112	0.080497
4-9-2-6-2	5.541115	0.166470
4-9-2-7-2	1.100223	0.116315
5-12-3-7-2	0.029130	$2.765557e^{-16}$
9-15-3-7-2	0.104942	0.067586
9-18-3-7-3	0.063275	0.038681
11-20-3-7-3	0.002018	$4.430892e^{-16}$
15-30-3-7-3	0.035528	0
15-30-3-10-3	0	$1.100223e^{-16}$

Table 8. MSI for large size

Average	**0.058898**	**$6.71e^{-16}$**
Problem characters (R-G-H-K-K_2)	NSGA-II	MOBA
15-35-3-10-3	0.110229	$5.541115e^{-16}$
16-36-3-10-3	0.024778	0
16-40-3-12-3	0.033006	$4.986003\ e^{-16}$
17-45-3-12-3	0.053920	$6.996226\ e^{-16}$
18-45-3-12-3	0.021001	$3.875780\ e^{-16}$
18-50-3-13-3	0.088690	$3.320669\ e^{-16}$
20-60-3-14-4	0.049846	$2.765557\ e^{-16}$
25-75-4-15-4	0.140881	$1.766356\ e^{-15}$
30-90-4-15-4	0.041908	$8.316672\ e^{-16}$
35-100-4-18-5	0.034718	$1.433289\ e^{-15}$

Table 9. Number of Pareto solutions and computational time for small size

	NPS		Computational time(s)	
Average	**2**	**1.9**	**73.41495**	**8.71821**
Problem characters (R-G-H-K-K_2)	NSGA-II	MOBA	NSGA-II	MOBA
3-7-2-5-1	2	1	43.71	2.304637
4-7-2-5-1	2	1	47.195905	2.930728
4-9-2-6-2	1	3	45.378222	3.814735
4-9-2-7-2	2	5	55.205583	4.498103
5-12-3-7-2	3	3	56.127584	4.665040
9-15-3-7-2	2	1	84.788409	11.088588
9-18-3-7-3	4	1	93.436604	13.718414
11-20-3-7-3	1	2	93.434902	13.325840
15-30-3-7-3	2	1	109.221109	13.119085
15-30-3-10-3	1	1	105.651202	17.716929

Table 10. Number of Pareto solutions and computational time for large size

	NPS		Computational time(s)	
Average	**2.8**	**2.2**	**631.545**	**267.2629**
Problem characters (R-G-H-K-K_2)	NSGA-II	MOBA	NSGA-II	MOBA
15-35-3-10-3	1	3	341.614671	60.098852
16-36-3-10-3	1	1	356.901229	100.831746
16-40-3-12-3	2	4	368.450320	143.406588
17-45-3-12-3	2	4	498.753348	240.982827
18-45-3-12-3	1	3	573.892324	191.820911
18-50-3-13-3	5	2	581.855149	302.749703
20-60-3-14-4	4	1	782.193048	394.199652
25-75-4-15-4	4	2	910.721841	515.944696
30-90-4-15-4	4	3	1053.405027	511.565098
35-100-4-18-5	4	1	847.667723	211.028653

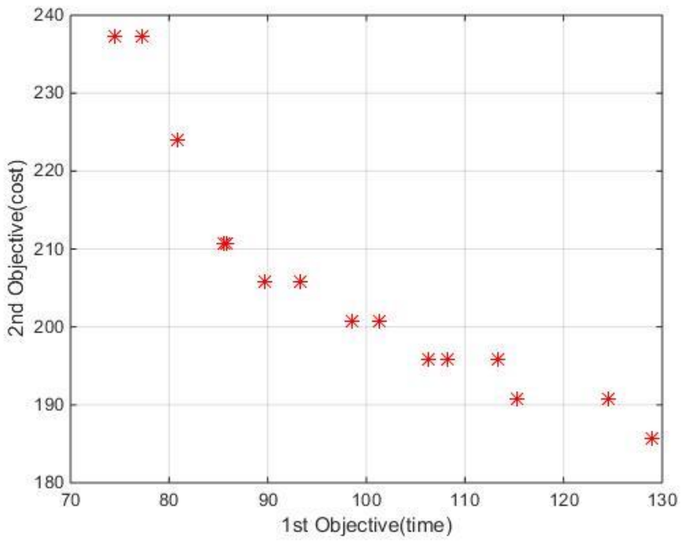

Figure 7. Example solution pareto for MOBA

In SM measure, according to the results and the average value of NSGA-II is more than MOBA. So, we can conclude that MOBA is superior to NSGA-II. In MID measure, the average value for NSGA-II in the small sizes is less than MOBA, so NSGA-II performs better than MOBA in small sizes and in the large size MOBA is better than NSGA-II. In MSI measure, according to the results and the average value of NSGA-II is less than MOBA. So, we can conclude that MOBA is superior to NSGA-II. The producing Pareto numbers NSGA-II is better than MOBA and MOBA is better than NSGA-II in computational time. In Figure 7 a solution with MOBA is shown.

6. Sensitive Analysis

Figure 8 represents the effect of changing the travel time on two objective functions and latest service completion time among all patients simultaneously. According to the results, increasing the travel time leads to a sharp increment of the first objective function. Because it is obvious that in this model any increase in time will lead to an increase in the latest service completion time among all patients and the first objective function. Also, as during raising travel time, ambulance service time increases and service cost of patient with ambulance increases.

Figure 9, shows impact of number of ambulances on objective functions and ambulances cost (left) and latest service completion time among all red and green code patients. According to numerical example, we considered two types of ambulances and totally five ambulances that located in hospitals. When the number of ambulances rise, it is clear that travel time and service time decrease and as shown, this lead to minimize the first objective function.

Also, in this case, using facilities and service of ambulance has increased, which means increment in the service cost of patient by ambulance that lead to increases the second objective function.

Figure 9 (left) shows latest service completion times E_r and E_g of red code and green code patients. Due to, the service of red code patients ends at their delivery to a hospital while the service of green code patients ends directly after having been treated in accident location, therefore as shown in the figure, the value of E_r is greater than the value of E_g .As expected, a larger number of ambulances results in a better service (lower objective 1 values). We see that the latest completion times of both red code patients and green code patients benefit from a medium number of ambulances.

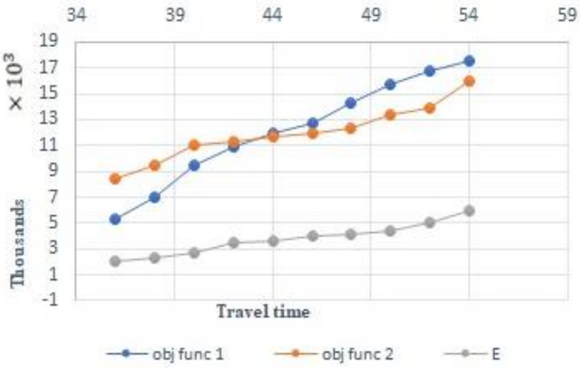

Figure 8. Trend of the objective functions under changes of travel time

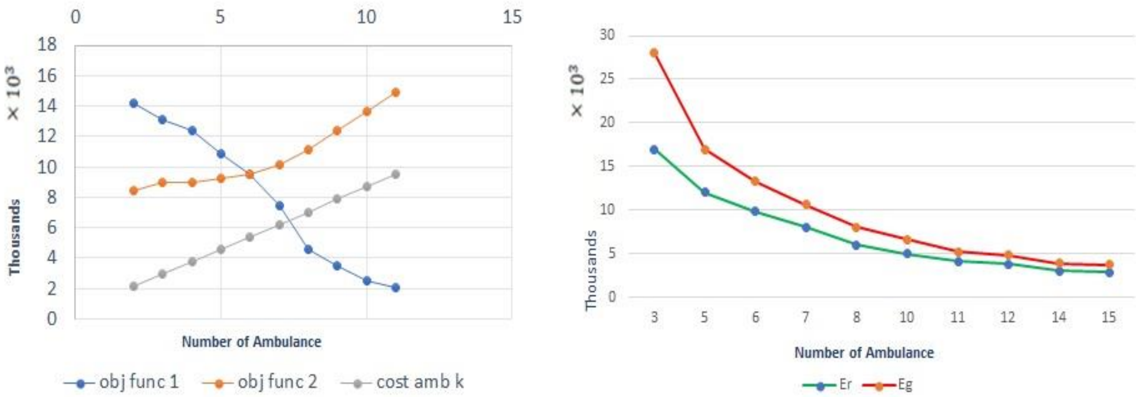

Figure 9. effect of number of ambulances on objective functions (left) latest service completion time for red and green patients (right)

In Figure 10, we examined the impact of a particular number of patients with different priorities. Due to importance of red code patients, we investigate rate of its changes. First, we consider $(w_r = w_g)$ in Figure 10 (left), it means red code patients have equal priority with green code patients. And then we consider different priority for them; $(w_r = 2,4,8,10)$, see Figure 10 (right). As expected, if the number of red code patients increases, the latest service completion time among these patients increases because the ambulances (regular and rescue helicopter) have to transfer more patients to the hospitals. Also, system costs increase. At the same time, as the service of green code patients ends directly after having been treated in the disaster location, the latest service completion time (E_g) of green code patients reduces, because fewer such patients need assistance.

In Figure 10 (right) it is clear that a higher value w_r indeed reduces the latest service completion time E_r of red code patients at the cost of the latest service completion time E_g of green code patients. Also, the first objective function, increases with a higher value of w_r, but this can be explained as this fact that the first objective function sums up the two weighted service completion times.

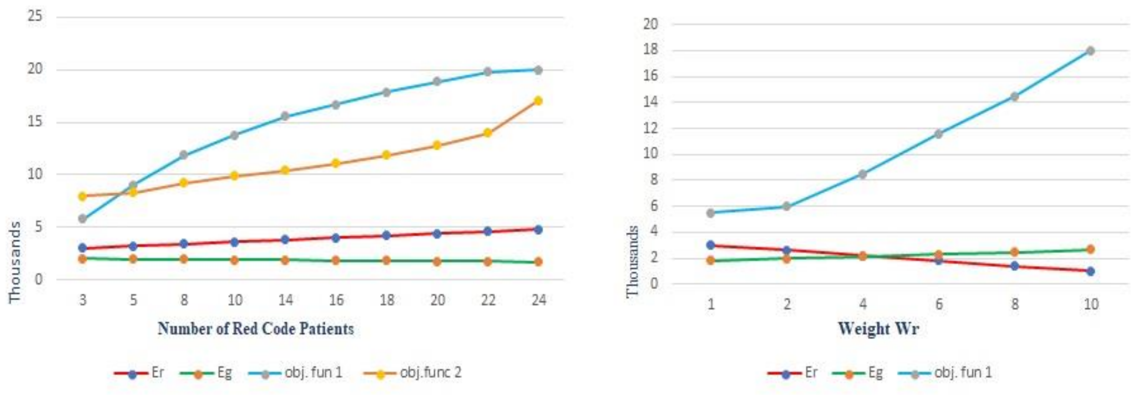

Figure 10. Sensitivity analysis of changes of the number of red code patients (left) weight w_r (right)

7. Conclusion

In this study a new approach for EMS vehicle routing problem for accident level response is investigated, where vehicles are considered different ambulances and rescue helicopter for serving patients. The cost and response time of EMS vehicles are different. The base accident level considered as disaster situation. As EMS faced with large number of patients, most of them with critical injuries, we proposed priority service to red cod patient. The aim of this study was reducing rate of mortality and morbidity. Therefore, we have proposed a new bi-objective ambulances routing problem by considering costs and total response times. The first objective minimized total response time by considering clustering patients and different EMS vehicle response time. The second objective minimized total EMS vehicles assignment costs. Optimum results of model are shown different optimum solutions for using them for decision makers in response phase and studies in mitigation phase. Augmented ε-constraint method is used for solving the exact model. As EMS vehicle routing have high frequency and unacceptably long time for responding phase of disasters. Therefore, improvement non-dominating sorting genetic (NSGA-II) and Multi Objective Bees Algorithm was proposed at the first time for solving model in very short response time. For validation solution approaches, first we compared metaheuristics with exact solution in small size. Then in large size compared NSGA-II and MOBA. The results were shown quality and computational response time of MOBA is better.

Future research for this study may consider parameters fuzzy. The data and processes have uncertainty. It could be considering different aspect of ambulances routing like time window, traffic, speed of ambulances, real blocking routs with detrition and etc. resilience approach may interest for this study. As we have seen with Shortage equippments and also the hospitals may destruct in disaster, considering temporary emergency stations in this model is so attractive (location routing problem). Considered model as a subset of set covering model is so interesting.

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