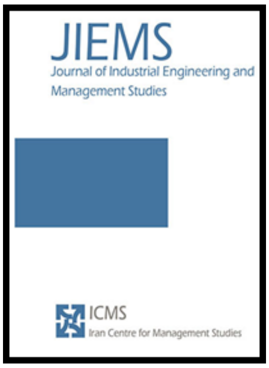
JIEMS

Journal of Industrial Engineering and Management Studies

Vol. x, No. x, x, pp. xx-xx

DOI: x

jiems.icms.ac.ir



A routing-allocation model for relief logistics with demand uncertainty: A genetic algorithm approach

Ali Bozorgi Amiri[1, *], Mostafa Akbari[2], Iman Dadashpour[3]

Abstract

Quick response to the relief needs right after disasters through efficient emergency logistics distribution is vital to the alleviation of disaster impact in the affected areas. In this paper, by focusing on the distribution of relief commodities after disaster, the best possible allocation for the affected areas is specified and shortest path to vehicle transporting is determined. The objective of the proposed model is the minimization of the maximum distance traveled by each vehicle in order to achieve fairness in response to the wounded. In our proposed model, the location of demand is uncertain and determined by the simulation approach. The proposed approach solves the proposed model and determines appropriate allocation and best route for vehicles according to the allocation, simultaneously. Consequently, using genetic algorithm with two-part chromosome structure in routing and allocation problems. Computational results show the efficiency and effectiveness of the proposed model and algorithm for solving real decision-making problems.

Keywords: emergency logistics; disaster; resource allocation; vehicle routing; genetic algorithm.

Received: February 2021-16

Revised: May 2021-08

Accepted: June 2021-28

1. Introduction

Nowadays, Natural disasters are considered as one of the most important factors around the world that endanger the lives of people. (Dellmuth. 2021) Thus, the global community has been forced to improve upon decentralization in accident management, effectiveness and accountability of risk management in natural disasters. (Putra and Matsuyuki, 2019) A pillar of human society has always been the effects of these natural or even unnatural disasters. Natural disasters usually affect everyone regardless of political or social standing. (Wang and Nie, 2019) The level of disaster and emergency is directly related to two factors: the type and size of the crisis and the performance and readiness of people before, during and afterwards. (Zhu et al., 2019). Tomasini and Van Wassenhove (2009) classified people into three groups

* Corresponding author; alibozorgi@ut.ac.ir

[1] School of Industrial Engineering, University of Tehran, Tehran, Iran.

[2] Department of Industrial and System Engineering, Amirkabir University of Technology, Tehran, Iran.

[3] Department of Industrial Engineering, College of Engineering, University of Tehran, Tehran, Iran.

after a crisis: The first group are people who are frightened and scattered outdoors, the second group are the injured or dead and the third group are people that are trapped but can be released with minimum effort. The main goal of this paper is How have been allocated relief station to crisis center and routing the vehicles after disaster. In this study, we focus on the first group that the location of the crisis requires such equipment as tents, water, food, etc. Caunhye et al. (2012) classified the main activities of emergency logistic to two groups: activities before and after the crisis. Activities that are carried out in the pre-crisis phase are 1. Facility location 2. Preparation of warehouse inventories 3. Discharge planning. Activities that are carried out after the crisis are: 1. Distribution of relief items 2. Transportation of the injured and the deceased 3. The evacuation of people. The topic of distribution of relief items is divided into two categories on its own: resource allocation and goods flow which are modeled in this case study. In this paper in response to the crisis phase, the sub-problem of allocation of relief stations to a crisis center and vehicle routing to distribute relief items has been modeled as mixed-integer programming problem. A proposed model implementation of the numerical example is carried out. Because the vehicle routing problem is NP-hard, a genetic algorithm is utilized to find a suitable answer to each question in a reasonable time. In each instance, the number of districts in crisis and relief stations are known. Each relief station has vehicles for the distribution of relief items. In the first phase of the model, the allocation of the mentioned vehicles to crisis area are determined. In the second phase, the best route for vehicles to the crisis centers are determined. (Fariborz. Y and Partovi, 2015) Routing practices used are designed such that each vehicle returns to the station it belongs to after it has given its services. In other words, routing is closed-loop. In fact, the main purpose of this article is to answer the question of what is the best route and where is the best location for the optimal distribution of relief items after the crisis. The remain of this paper is organized as follows: In section 2, the previous studies have been reviewed. The description of the problem and the proposed mathematic model are investigated in section 3. The proposed solution approach is presented in section 4, and computational results are provided in section 5. Finally, the conclusion and suggestions for future studies are discussed in section 6.

2. Literature review

This section is focused on post-disaster measures as well as the distribution of aid, routing, and allocation. The first research on disaster response was carried out by Knott (1998) with a linear programming model for determining the scheduling of the vehicle for bulk food transportation in disaster areas. Oh and Haghani (1996) analyzed the transportation of large volumes of goods such as food, clothing, medical equipment, medicines, machinery and human resource in an efficient manner to minimize the casualties with several types of vehicle for relief operations. One point which had been ignored in this subject for many years is the lack of availability of transportation routing access to roads in the early hours of the relief operation, which Barbarosoghlo et al. (2002) in an article considers this objective to focus on using a helicopter. Barbarosoghlo and Arda (2004) modeled the problem as a Bi-level stochastic programming problem to plan the delivery of aids. Due to the essence of demand, the considered demand as a stochastic variable, which is only considered in demand. Ghasemi and Babaeinesami (2020) proposed a model to focus on fire station material optimization and decrease the time of arrive the occurrence. They were use the enterprise dynamic software for simulation the fire station situation. Yi and Kumar (2006) considered the main problem of emergency logistic. The evacuation of injured and the distribution of relief items are highlighted in their paper. They divided this problem into two stages of decision making that includes determining vehicle routing structure and distribution of goods and didn’t consider any uncertainties. They utilized the Ant colony optimization meta-heuristic method for solving their model. Sheu (2007) modeled the distribution relief items problem from production centers to distribution centers and crisis areas using a dynamic approach and time-dependent modeling and used a fuzzy clustering technique to solve it. Yi and Ozdamar (2007) proposed a model for coordination of logistics in emergencies. This model studies two issues: 1) Optimum location of emergency responders. 2) efficient distribution of medical units. In this model, a mixed integer bi-level network flow has been utilized. A two-stage methodology is proposed for solving this problem: 1) Formulation of the model. 2) an algorithm which produces routing and instructions on loading/unloading from the optimum solution of the previous stage. In Yi's study, dealing with uncertainty has been avoided. Saadatseresht et al. (2008) presented a model for evacuation and transference of the people from disaster areas to a safe place to discover the best route and minimum distance. Some of the techniques used in this study include Multi-objective evolutionary algorithms and geographic information systems. They offered a three-level method for modeling the evacuation problem. In this way, the location Relief stations must first be determined, then the allocation of the stations to crisis centers considering the restrictions and finally using an algorithm, determining the optimum routing between each crisis center and relief station assigned to it. Zografos and Androutsopoulos (2008) proposed a decision support system in the presence of an uncertain environment with a special focus on the routing of dangerous material and the consideration of time of the transfer, the concepts of risk and discharge. The aim of this study was finding the best routing for transferring dangerous materials through modeling the problem as an integer programming and solving it by using the Lagrange relaxation heuristic algorithm. Yueming and Deyun (2008) examined the role of emergency evacuation plans of urban transit system's ability to respond in a disaster situation. Examined the role of emergency evacuation planning on optimization of the capabilities of urban transit systems in responding to the disaster. They considered the structure of evacuation routing and distribution networks and aimed to achieve the shortest time for emergency responses. Erdemir et al. (2010) studied a combining of ground and air medical services and proposed a combined model to cover the crisis area. They used heuristic methods for solving their model. Ozdamar and Demir (2012) focused on the post-disaster phase and modeled the problems of distributing relief items and evacuating the injured and solved these by utilization of a hierarchical clustering method. Bozorgi-Amiri et al. (2013) introduced a multi-objective robust stochastic programming under uncertainty. They considered demand, supply, and the cost of buying and shipping of their proposed stochastic model and utilized a scenario-based approach. Najafi and Eshghi (2013) considered the shipment of goods and injured, as well as the ability to carry different vehicles in their proposed model. Najafi et al. (2013) proposed a robust multi-objective model by considering several vehicles, several goods, and several periods with the aim of logistics operation management of people in crisis and relief after the earthquake. Che et al. (2014) proposed a bi-level optimization model by applying uncertainty to demand. Their model consisted of lower and upper which, the aim of the upper model was minimizing the last arrival time and maximizing the utilization of vehicle load and solved it by genetic algorithm, and the aim of other one was minimizing the cost of total transportation and employed the Gams to solved it. Haijun Wang et al. (2014) created a nonlinear open location routing problem for relief distribution, which, this model included the travel time, total cost, and reliability divided at delivery time. Bozorgi-Amiri and Khorsi (2015) proposed a dynamic multi-objective location–routing model for relief logistic planning under uncertainty on demand, travel time and cost parameters which, in that paper, they were considered condition before and after disasters and solved their model by used on ε-constraint method. Ahmadi et al. (2015) for a multi depots' location routing problem proposed a model with due to the failure network, location of depots, and standard time. Their model defined the location of local depots and distribution routing after an earthquake. Christian Burkat et al. (2016). Studied in the decision support system and proposed the origin of beneficiaries' choice for the disaster relief logistics in the location routing problem, in these regards they were introduced a multi-objective location routing model which this model could minimize the out of service demand and the DC's cost for routing the relief shipment. Vahdani et al. (2016) introduced a new mathematical integer nonlinear multi-objective, multi-period, multi-commodity model to determine the distribution center for on-time dispensation the relief's items to the crisis area, vehicle routing, etc. which their model aim is minimizing the travel time and total cost. For solving the model, they apply two metaheuristic algorithms, namely NSGAII and MOPSO. Saffarian et al. (2017) investigated on a model that includes the multi-objective model for location and routing of vehicles in disaster. In this model, uncertainty in transfer time and demand of warehouse in the disaster area. Vahdani et al. (2018) considered a unique system with split delivery that takes several services in the critical area when the disaster takes place. They used the two metaheuristic algorithms NSGAII and MOPSO to solve their proposed model when some parameters in it put on uncertainty conditions.

Barojas et al. (2019) proposed a mixed integer non-linear model that it provides necessary materials for the respectable survival of the people, usually in the hydro meteorological disasters of the state of Veracruz., Mexico.

Doodman et al. (2019), considers the problem for improving performance in the humanitarian relief chain, that including the removal of relief items and planning for a multi - period distribution between distribution centers. In addition to improving supply chain cost, their proposed model also increased equality and equity.

Adabazadeh et al. (2020) evaluated the performance of health unit by consider population, GDP, etc. by statistical method in dealing the covid-19. In fact, the goal of this paper is identifying the capabilities of government behavior in critical management on pandemic time. Other works and comparison have been shown in table 1.

The gap analyze is shown the researcher often considers uncertainty for the demand's volume of relief goods in the post-disaster phase and pay no attention to uncertainty instead of demand. As a result, the topics of routing and allocation of relief items with uncertainty in demand's place will be discussed in this article. Another point is that previous research on this topic focuses on the response time to a crisis, often aiming to minimize this time; while the realities of a relief logistics system are establishing equity and justice in response times. So, this article utilizes the minimax objective function in order to achieve minimization of maximum distance by each vehicle for establishing justice in response to injured. Due to the complexity of the problem being of the exponential degree, with the increasing in the scale of the problem, a lot more time is required to get an accurate answer; therefore, we utilize a metaheuristic approach for solving this model.

Table 1. literature review

Authors	Issue					Objective function		Method of solution
	SCM	Routing	Scheduling	Location	Allocation	Single	multi	
Liu et al., (2019)		*		*			*	HHA and NSGA-II algorithms
Peng et al., (2019)	*							PLS-SEM
Cao et al., (2017)	*			*			*	Branch and Bound
Sekar et al., (2019)		*					*	Nash Equilibrium
Bozorgi amiri & Khorsi (2016)		*		*	*		*	ε-constraint
Caunhye et al., (2015)	*	*		*		*		Expected-value model
Cavdur et al., (2016)					*	*		deterministic model stochastic program
Ghasemi et al., (2019)				*	*		*	MMOPSO, NSGA-II, ε-constraint
Ayough et al., (2020)		*				*		Time window, SA, 3L-CVRP
Rafie-Majd et al., (2018)	*	*			*	*		Lagrangian relaxation algorithm
Tofighi et al., (2016)	*						*	Mixed possibilistic-stochastic programming;
Vahdani et al., (2018)		*		*			*	NSGAII and MOPSO Robust
Elluru et al., (2019)	*	*		*		*		proactive and reactive approaches
Ghaffari et al., (2020)	*		*					swarm optimization algorithm
Liu et al., (2020)					*			PSO-RFR
Kebriyaii et al., (2021)	*							Robust fazzy stochastic programming
Sun et al., (2021)				*	*	*		Robust
Rabbani et al., (2021)		*					*	NSGA-II MOPSO
Current work		*			*	*		Genetic algorithm

3. Problem description and proposing a mathematic model

This problem consists of some relief stations with specific capacity and crisis area with an uncertain location. The location of relief stations is available, and the demand for relief items such as tents, canned food, and water are only calculated for areas with no certain coordinates which are obtained through simulations. The location of relief stations has been identified, and demand for relief items such as tents, canned food, and water for crisis areas with no certain coordinates is calculated using simulation. As is apparent in Figure 1 the logistics planning for the distribution of relief items consists of four steps which in this study, we assume that the first step is determined therefore decisions are only made regarding steps two to four.

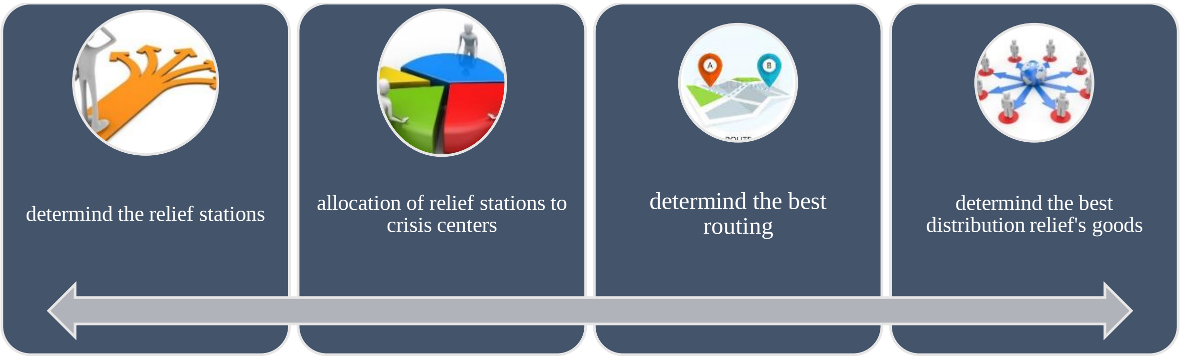


Figure 1. Steps of emergency logistics planning

3.1. Assumption

1. Land-based transportations are being considered.
2. Relief stations are fixed, and they have unlimited capacity.
3. Demand for relief and rescue operations are determined in crisis centers.
4. Each relief station has one vehicle for shipment of goods.
5. The dimensions and severity of the incidents are such that paths between all relief centers and crisis centers are available, as well as between all the crisis centers ensuring no failures.
6. Allocation of each crisis center only to one vehicle, but each vehicle can service several crisis centers.

3.2. Indices, parameters, and variables

N	: set of crisis points
M	: set of relief stations
V	: number of vehicles for relief items transport
Pos_i	: coordinates of crisis point i $(i \in N)$
$Pos0_j$	: coordinates of relief station j $(j \in M)$
d_{ij}	: the distance of crisis points i with the coordinate of Pos_i from crisis point j with the coordinate of $Pos0_j$
$d0_{ij}$	: the distance of crisis points i from relief station j $(i \in N \;\; j \in M)$
D_i	: the demand of crisis points i $(i \in N)$
C_v	: the capacity of vehicle v $(v \in V)$
y_{iv}	: Equals 1 if vehicle v is allocated to crisis point; otherwise, equal to 0
X^m_{ijv}	: Number of trips between crisis point i to crisis point j by vehicle v from relief station M

3.3. Mathematical model

$$Min\ Z = Max_v(\sum_{m=1}^{M}\sum_{j=1}^{N}\sum_{i=1}^{N} d_{ij}\, X_{ijv}^{m} + \sum_{m=1}^{M}\sum_{j=1}^{M}\sum_{i=1}^{N} d0_{ij}\, X_{ijv}^{m}) \quad (1)$$

$$\sum_{v=1}^{V} y_{iv} = 1 \qquad \forall i \in N \quad (2$$

$$\sum_{i=1}^{N} D_i y_{iv} \leq C_v \quad \forall v \in V \quad (3)$$

$$\sum_r X_{rjv}^{m} = \sum_s X_{jsv}^{m} \quad \forall j.v.m \neq j\ .y_{jv} = 0 \quad (4)$$

$$X_{ijv}^{m} \geq 0 \qquad \forall i.j.v.m \quad (5)$$

$$X_{ijv}^{m} = integer \quad \forall i.j.v.m \quad (6)$$

$$y_{iv} = 0.1 \qquad \forall i.v \quad (7)$$

The objective function of this problem (equation 1) minimizes the maximum distance traveled by vehicles. For this purpose, the distance traveled by each vehicle is calculated, and among them, the maximum value is selected and considered as the objective function's value. Constraint (2) ensures that each crisis center is only allocated to one vehicle. Constraint (3) ensures that the demand quantity allocated to a vehicle does not exceed its capacity. Constrain (4) represent the equilibrium equation of the number of entries and exits to and from each crisis center constraint (5) -(7) are related to nonnegative, integer, and 0-1 variable constraints.

4. The proposed solution approach

Due to the vehicle routing problem being an NP-Hard, using exact methods on some relatively large-scale problems cannot be justified (Lenstra and Kan, 1981). To solve the proposed model, the genetic algorithm, which is one of the evolutionary metaheuristic algorithms is utilized. Jan Holland proposed of the genetic algorithm as one of the evolutionary algorithms (Holland, 1975). A genetic algorithm is a searching algorithm based on the structure of genes and chromosomes. It is one of the random search methods, and despite the randomness quality, it has a goal-oriented structure. In this regard, Figure 2 is an overview of the proposed solution algorithm.

4.1. Chromosome's description

The structure of the Chromosome is a two-part structure such that in the first part of this structure, the assignment of crisis bases to relief centers is determined, and the second part consists of the order by which each vehicle visits a disaster area.

4.2. Initial population

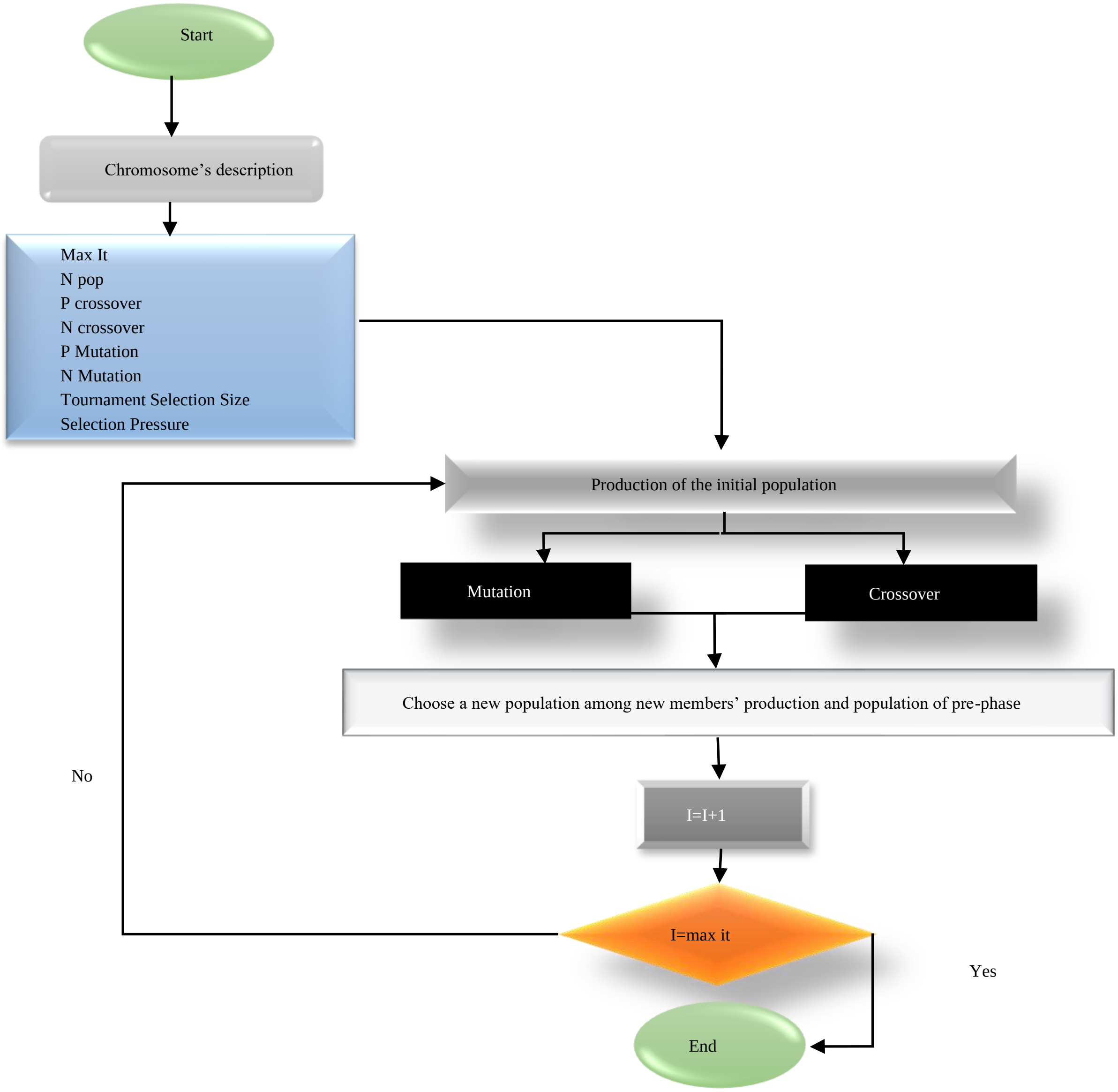
A function is used for generating the initial population, which randomly determines the allocation of vehicles and arrangement of crisis centers. In addition, a penalty method is used for the enforcement of restrictions.

4.3. Cross over operation

Figure 3 describes the two types of crossover operations, one of them relating to the first part of the chromosome and the other for the second part of it. The crossover considered for part one is a single-point crossover, and the crossover applied to the second part is a permutation crossover. With every iteration of the crossover operation, it's either done so on the first section only, or on the second section, or both of them. For example, if there are five vehicles and ten crisis centers, performing a single-point crossover, we will have to perform a single-point crossover.

4.4. Mutation operation

To mutation, operation is defined as two types of mutation: one for the first part of chromosome related to the allocation of vehicles and another for the second part of, the arrangement of crisis centers. For each mutation operation, one member of the population is randomly selected, then the first part mutation is calculated by choosing a crisis center randomly and is allocated to a vehicle that is not the vehicle which it is currently being served by. For a mutation will be considered the second part of the chromosome by using of switch defined, one of the following scenarios occurs: The mutation for the second part of the chromosome is defined using the switch property and results in one of these scenarios:



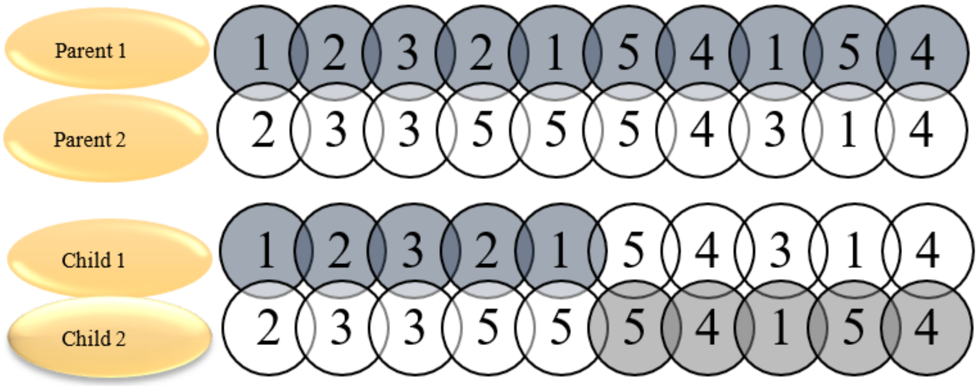


Figure 3. Single-point cross over

1- Swap Mutation: swaps the location of two crisis centers in the chromosome structure. 2- Reversion Mutation: The number of two genes are accidentally chosen, and the number of crisis centers between these two genes is reversed. 3- Insertion Mutation: Number of two genes are randomly selected, and the number of the crisis center related to the second gene is placed immediately after the first gene. For example, there are five vehicles and ten crisis centers, by doing mutation operations on the first part of the chromosome, we will have:

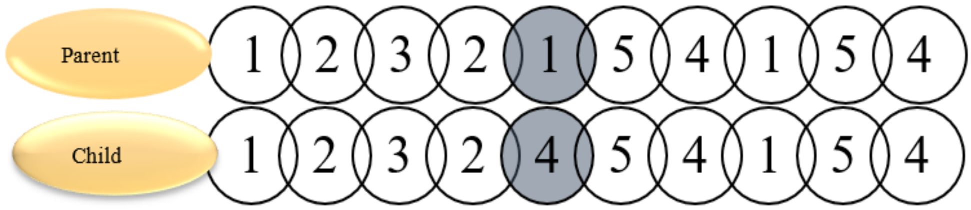


Figure 4. A mutation in the first part of the chromosome

By randomly choosing box number 5, the number “1” in that box is replaced by another number.

4.5. Choosing a new population

In order to choose a new population, at first, all of the population produced from mutation and crossover operations is combined with the initial population. Then the population calculated is sorted by the cost function, and finally they are ordered by the number of initial population (npop) and the members with the best cost function are chosen.

4.6. Parameters setting and stop condition

In this section, the parameters of the genetic algorithm as well as tuning processes are expressed.

- MaxIt: The maximum number of repetitions of the main loop of the algorithm.
- Npop: the initial population.
- P Crossover: Percent of the population on which a crossover operation was performed.
- P Mutation: Percent of the population, on which mutation was performed.
- Tournament Selection Size: Represents the number of chromosomes that must be chosen to produce a member of the next generation. The best of these chromosomes are chosen.
- Selection Pressure: selection pressure refers to the concept of the best chromosomes spreading faster and on a greater scale.

By implementing this algorithm repeatedly and using the results of previous studies, parameters of the algorithm are set to the following values. Stopping criteria chosen in our code is the maximum number of iterations.

Max It	=200
N pop	=50
P Crossover	=0.8
N Crossover	Round= (p Crossover * n pop/2) *2
P Mutation	=0.3
N Mutation	Round= (p Mutation * n pop)
Tournament Selection Size	=3
Selection Pressure	=10

5. Computational results

To represent the performance and efficiency of the model and proposed solution method, this is implemented on several sample problems, some of them by considering the opinion of red crescent organization experts and others are random based on similar research. which are discussed in more detail in the table (2) in below:

Table 2. Sample problem profile

A Sample problem	The number of crisis (N)centers	The number of Relief station (M)	The number of vehicles(V)	Capacity of vehicles(C)
1	40	5	5	563,393,531,474,456
2	50	8	8	461,453,366,374,423,232,361,307
3	80	10	10	589,401,474,395,389,588,587,538,555,367
4	100	12	12	680,440,616,363,413,666,447,531,623,520,692,376
5	130	14	14	444,538,378,750,599,404,608,786,759,444,490,622,486, 767
6	180	18	18	702,672,473,346,581,385,714,349,562,553,701,772,479, 354, 373,758,608,525
7	200	20	20	420,710,618,800,742,411,482,386,695,526,633,627,734, 598, 589,521,549,534,779,531

The demand of each crisis center is determined according to the population density of the center, event severity, and types of buildings in the area. Table 3 represents the demand only for the first sample (consisting of forty crisis centers). For example, the demand for the first crisis center equals 86 units of goods.

Table 3. The demand for a crisis center for the first sample problem

Crisis center number(N)																			
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Summation of demand for each crisis center																			
86	92	98	55	34	19	55	62	78	17	69	56	25	94	63	49	94	69	50	85

Crisis center number(N)																			
21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
Summation of demand for each crisis center																			
57	59	71	43	31	62	88	46	20	49	37	46	85	46	45	42	22	33	17	48

Applying the proposed solution method on the before mentioned problem and solving the model by use of the genetic algorithm, reach the results presented in Table 4 containing the objective function values and computing time. The proposed solution approach was coded in MATLAB, and the computer used for calculations supported a Pentium ® Dual-Core with 3GHz CPU and 4 GB of internal storage capacity.

Table 4. Function value and solving time of sample problem

A Sample problem	Function value (Z)	model solving time(Second)	The initial population	The maximum number of repetitions main loop
1	286	10,260	50	200
2	305	19,865	50	200
3	422	14,990	50	200
4	454	18,059	50	200
5	478	20,309	50	200
6	560	33,344	50	200
7	634	27,043	50	200
8	648	36,597	50	200
9	665	45,297	50	200
10	680	55,628	50	200
11	696	58,955	50	200
12	705	62,265	50	200
13	718	74,654	50	200
14	729	87,996	50	200
15	741	98,234	50	200
16	758	106,235	50	200
17	771	110,384	50	200
18	789	116,547	50	200
19	804	119,258	50	200
20	822	121,402	50	200
21	843	124,928	50	200
22	867	125,368	50	200
23	891	128,641	50	200
24	912	131,260	50	200
25	934	132,825	50	200
26	956	138,564	50	200
27	995	139,211	50	200
28	1010	141,405	50	200
29	1048	143,657	50	200
30	1066	147,288	50	200
31	1097	148,054	50	200
32	1115	148.897	50	200
33	1138	150,023	50	200
34	1161	152,083	50	200
35	1182	152,558	50	200
36	1198	153,091	50	200
37	1208	154,334	50	200
38	1225	155,103	50	200
39	1253	155,997	50	200
40	1269	157,199	50	200

Table 5 shows the allocation of the relief stations to the crisis centers for the first crisis center (containing forty crisis centers and five relief stations). For example, the first column shows that the 9th crisis center was allocated to the 2nd relief station.

Table 5. How to allocate the relief station to the crisis center for first sample problem

Relief station number	Crisis center number
1	32,7,33,13,30,36,25,37,17
2	9,11,19,14,15,22,29,38
3	39,21,18,27,31,24,2
4	16,6,10,5,1,26,23
5	4,2,28,3,34,40,35,12,8

In addition, Table 6 shows the order by which each crisis center is visited by each vehicle in the first sample problem. For example, according to the first row, the first vehicle visits crisis centers number 32,7,33,13,30,36,25,37,17 respectively.

Table 6. Arranges to meet up a crisis center in the first sample problem

vehicle	Arrange to meet up crisis centers
1	32,7,33,13,30,36,25,32,17
2	9,11,19,14,15,22,29,38
3	39,21,18,27,31,24,2
4	16,6,10,5,1,26,23
5	4,20,28,3,31,40,35,12,8

5.1. Sensitivity analysis

5.1.1. GA algorithm

The proposed genetic algorithm has six parameters, Max It ‹N pop ‹P Crossover ‹P Mutation, Pressure Selection (PS) and Size Selection Tournament (SST). The most important parameters are mutation and crossover that will be set by changing and recording the results. In order to tune the rate of crossover and mutation parameters, the value of the objective and the time for solving the model are compared in three different states: the crossover rate is greater than the mutation rate, the two rates are equal, and the crossover rate is lower than the mutation rate. The best answer is given by solution time in the first state. Selection Pressure and Selection Size are related to intensification and diversification of features of the algorithm, which are calculated after their values are changed, and the convergence of the algorithm is observed. To tune these two parameters the maximum number of iterations and the initial population, the speed with which the algorithm proceeds decrease tremendously with the increase in initial population size, but the quality of the results improves. With the increase in the number of iterations, it is observed that after some number of iterations, improvements in the solution is slow and minimal. Therefore, considering the three factors of quality of the solution, time to reach the solution, and the maximum number of iterations in which the solution is fixed; the two parameters are specified. In what follows, sensitivity analysis is done on the results of the sample problem in three states expressed through crossover and mutation rates.
As shown in Table 7, the quality of solutions in the case where the crossover rate is higher than mutation's is higher. Moreover, the time it takes to reach the solution is longer, but given the higher quality of the solution found and the importance of this factor; the optimized solution for the parameters is the second row in the previous table.

Table 7. Sensitivity analysis

Max It	N Pop	P Crossover	P Mutation	SP	aT SS	Function value	Time solution(second)
200	50	0.9	0.3	10	3	297	11,31
200	50	0.8	0.3	10	3	286	10,26
200	50	0.6	0.3	10	3	305	9,22
200	50	0.5	0.3	10	3	321	9,01
200	50	0.5	0.5	10	3	355	8,99
200	50	0.7	0.7	10	3	349	10,58
200	50	0.8	0.8	10	3	331	15,03
200	50	0.3	0.9	10	3	292	9,21
200	50	0.3	0.8	10	3	369	8,77
200	50	0.3	0.6	10	3	341	8,52
200	50	0.3	0.5	10	3	368	8,11

The convergence of the proposed algorithm is shown in Figure 5. As apparent by the figure, increasing the number of repetitions of the implementation of the genetic algorithm, objective function's values decrease, and after iteration 140, there is no longer a change in the objective function value, and the problem has converged.

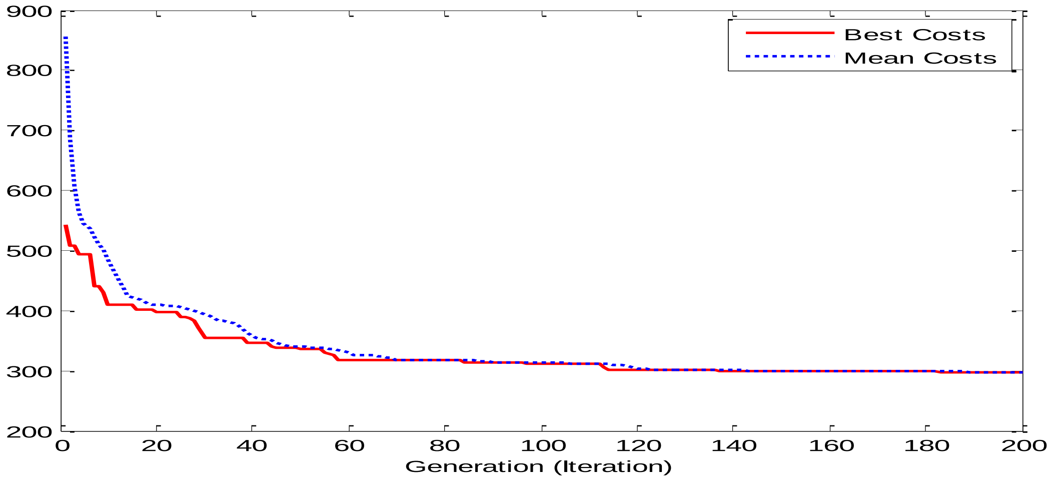


Figure 5. Show how the convergence of the algorithm

5.1.2. Demand

We solve the problem with different amount of demand in variance of -20%, -10%, base case, 10%, 20% for checking the effect of demand on the objecting function behavior. Result of sensitivity on demand has been shown in Figure 6. Due to the Figure 6, 10% tolerance in demand cannot has an effect in objective function. On the one hand decreasing the 20% in demand leads to increase 14% in objective function and on the other hand decreasing 20% can decrease 16%.

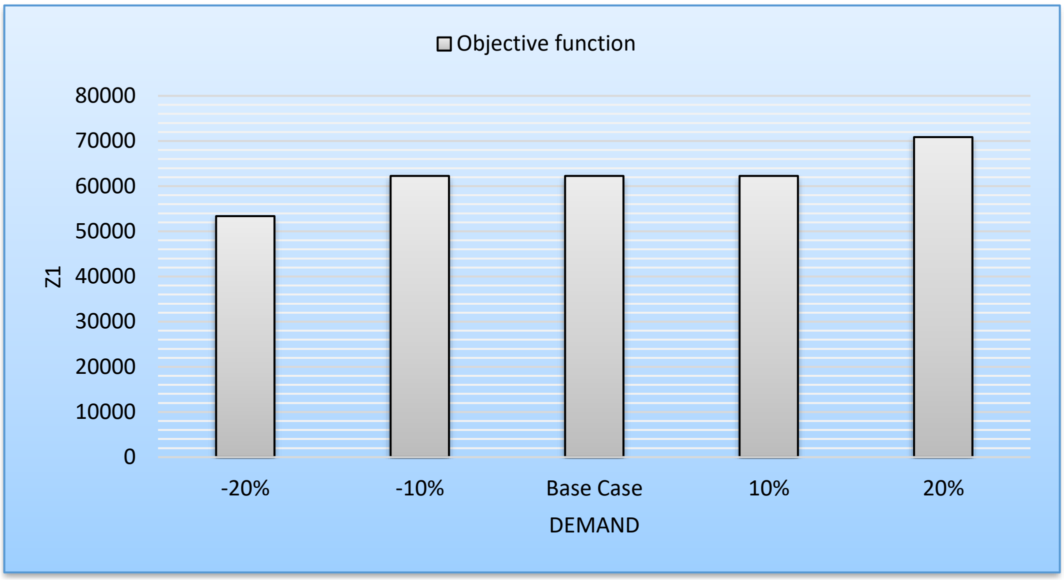


Figure 6. The demand's effect on the objective function

5.1.3. Capacity of vehicle

In this section, investigate the capacity of vehicles tolerance in this problem. Different value of capacity and results are analyzed for this model. Figure 7 shown the resulted of vehicle capacity's sensitivity analysis. This figure is shows clearly that by decreasing of capacity leads to increasing the objective function and vice versa.

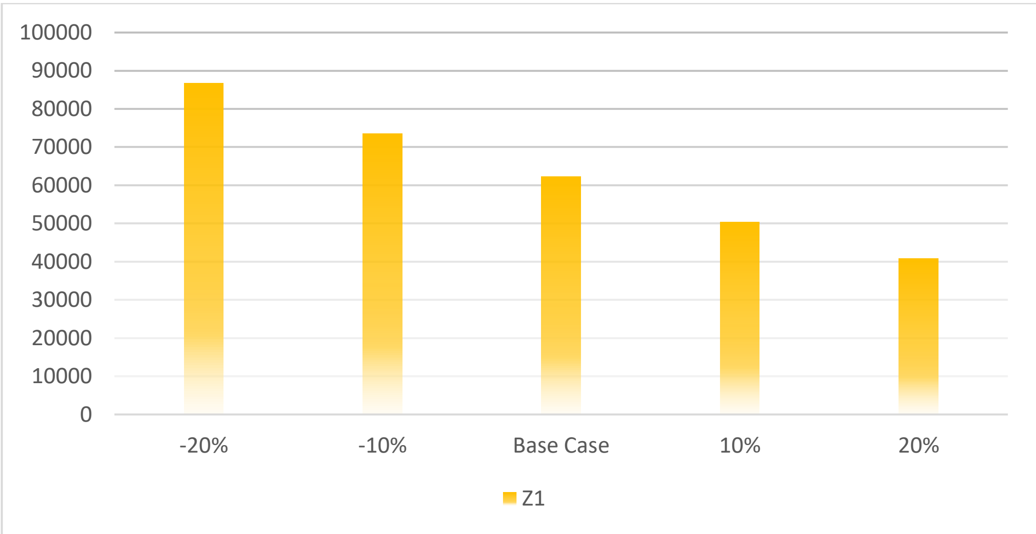


Figure 7. The vehicle capacity effect on the objective function

6. Conclusions

Synchronization of logistics after a crisis is an operational level decision and needs to be made and adopted promptly, which is why in this paper a genetic metaheuristic algorithm is used that proposes an appropriate response for the vehicle routing problem and allocation of relief stations to crisis centers in a short time while considering in-demand location uncertainty. The GA algorithm simultaneously solves the allocation and routing problems using a bi-level chromosome structure and through several kinds of mutations and crossovers for optimization of proposed model. Implementation of this method on several sample issues concluded that the solution has highly acceptable results and functionality, therefore can be used by planners and officials of organization after a crisis has occurred. Since the genetic algorithm used is population-based, this model is suitable for problems that are compounds with several states. For future studies, the authors suggest dynamic routing of the same model could be used for more accurate results which can be solved using a simulation-optimization technique. simultaneous consideration of uncertainty in location and demand, planning for other types of survivors, road destructions and use of different vehicles are other topics for future research.

Reference

Adabavazeh, N., Nikbakht, M., and Amirteimoori, A., (2020). "Envelopment analysis for global response to novel 2019 coronavirus-SARS-COV-2 (COVID-19)", *Journal of Industrial Engineering and Management Studies*, Vol. 7, No. 2, pp. 1-35.

Ahmadi Morteza, Seifi Abbas, Behnam Tootooni, (2015). "A humanitarian logistics model for disaster relief operation considering network failure and standard relief time: A case study on San Francisco district", *Transportation Research Part E,* Vol.75, pp. 145–163.

Ayough, A., Khorshidvand, B., Massomnedjad, N., and Motameni, A., (2020). "An integrated approach for three-dimensional capacitated vehicle routing problem considering time windows", *Journal of Modelling in Management*.

Barbarosoglu, G., Ozdamar, L., and Cevik, A., (2002). "An Interactive Approach for Hierarchical Analysis of Helicopter Logistics in Disaster Relief Operations", *Eur. J. Operation Res.*, Vol. 140, pp.118–133.

Barbarosoglu, G.Y., and Arda, Y., (2004). "A Two-stage stochastic programming framework for transportation planning in disaster response", *Journal of the Operational Research Society*, Vol. 55, pp. 43-53.

Barojas-Payán, E., Sánchez-Partida, D., Martínez-Flores, J.L., and Gibaja-Romero, D.E., (2019). "Mathematical Model for Locating a Pre-Positioned Warehouse and for Calculating Inventory Levels", *Journal of Disaster Research*, Vol. 14, No. 4, pp. 649-666.

Bozorgi-Amiri, A., and Khorsi, M., (2015). "A dynamic multi-objective location–routing model for relief logistic planning under uncertainty on demand, travel time, and cost parameters", *The International Journal of Advanced Manufacturing Technology*, Vol. 85, No. 5, pp. 1633–1648.

Bozorgi-Amiri, A., and Khorsi, M., (2016). "A dynamic multi-objective location–routing model for relief logistic planning under uncertainty on demand, travel time, and cost parameters", *The International Journal of Advanced Manufacturing Technology*, Vol. 85, No. 5, pp. 1633-1648.

Bozorgi-Amiri, A., Jabalameli, M.S., and Mirzapour Al-e-Hashem, S.M.J., (2013). "A multi-objective robust stochastic programming model for disaster relief logistics under uncertainty", *OR Spectrum*, Vol. 35, pp. 905–933.

Burkart Christian, C., Nolz Pamela, J., and Gutjahr, Walter., (2016). "Modelling beneficiaries' choice in disaster relief logistics", *Springer Science+Business Media New York*.

Cao, C., Li, C., Yang, Q., and Zhang, F., (2017). "Multi-objective optimization model of emergency organization allocation for sustainable disaster supply chain", *Sustainability*, Vol. 9, No. 11, pp. 2103.

Caunhye, A. M., Zhang, Y., Li, M., and Nie, X., (2016). "A location-routing model for prepositioning and distributing emergency supplies", *Transportation research part E: logistics and transportation review*, Vol. 90, pp. 161-176.

Caunhye, A.M., Nie, X., and Pokharel, S., (2012). "Optimization models in emergency logistics: A literature review", *Socio-Economic Planning Sciences*, Vol. 46, pp. 4-13.

Cavdur, F., Kose-Kucuk, M., and Sebatli, A., (2016). "Allocation of temporary disaster response facilities under demand uncertainty: An earthquake case study", *International Journal of Disaster Risk Reduction*, Vol. 19, pp. 159-166.

Chen, G., Zhang, J., Fu, J.-Y., (2014). "Multi-objective fuzzy location-allocation-routing problem in urgent relief distribution system", *Journal of Transportation Systems Engineering and Information Technology*, Vol. 14, No. 4, pp. 160-167.

Dellmuth, L.M., Bender, F.A.M., Jönsson, A.R., Rosvold, E.L., and von Uexkull, N., (2021). "Humanitarian need drives multilateral disaster aid", *Proceedings of the National Academy of Sciences*, Vol. 118, No. 4.

Doodman, M., Shokr, I., Bozorgi-Amiri, A., and Jolai, F., (2019). "Pre-positioning and dynamic operations planning in pre-and post-disaster phases with lateral transhipment under uncertainty and disruption", *Journal of Industrial Engineering International*, pp. 1-16.

Elluru, S., Gupta, H., Kaur, H., and Singh, S.P., (2019). "Proactive and reactive models for disaster resilient supply chain", *Annals of Operations Research*, Vol. 283, No. 1, pp. 199-224.

Erdemir, E.T., Batta, R., Rogerson, P.A., Blatt, A., and Flanigan, M., (2010). "Joint ground and air emergency medical services coverage models: A greedy heuristic solution approach", *European Journal of Operational Research*, Vol. 207, No. 2, pp. 736-749.

Ghaffari, Z., Nasiri, M.M., Bozorgi-Amiri, A., and Rahbari, A., (2020). "Emergency supply chain scheduling problem with multiple resources in disaster relief operations", *Transport metrica A: Transport Science*, Vol. 16, No. 3, pp. 930-956.

Ghasemi, P., and Babaeinesami, A., (2020). "Simulation of fire stations resources considering the downtime of machines: A case study", *Journal of Industrial Engineering and Management Studies*, Vol. 7, No. 1, pp. 161-176.

Ghasemi, P., Khalili-Damghani, K., Hafezalkotob, A., and Raissi, S., (2019). "Uncertain multi-objective multi-commodity multi-period multi-vehicle location-allocation model for earthquake evacuation planning", *Applied Mathematics and Computation*, Vol. 350, pp. 105-132.

Holland, J.H., (1992). "Adaptation in natural and artificial systems", *Ann Arbor, MI: University of Michigan Press.*

Kebriyaii, O., Hamzehei, M., and Khalilzadeh, M., (2021). "A disaster relief commodity supply chain network considering emergency relief volunteers: a case study", *Journal of Humanitarian Logistics and Supply Chain Management.*

Knott. R, (1988). "Vehicle Routing for Emergency Relief Management: A Knowledge-based Approach", *Disaster*, Vol. 12, pp. 285–293.

Lenstra, J.K., and Rinnooy Kan, A.H.G., (1981). "Complexity of vehicle and scheduling problem", *Networks*, Vol. 11, pp. 221-227.

Liu, C., Kou, G., Peng, Y., and Alsaadi, F.E., (2019). "Location-routing problem for relief distribution in the early post-earthquake stage from the perspective of fairness", *Sustainability*, Vol. 11, No. 12, pp. 3420.

Najafi, M., and Eshghi, K., (2013). "A logistics planning model to improve the response phase of earthquake", *International Journal of Industrial Engineering and Production Management*, Vol. 23, No. 4, pp. 401-416.

Najafi, M., Eshghi, K., and Dullaert, W., (2013). "A multi-objective robust optimization model for logistics planning in the earthquake response phase", *Transportation Research Part E*, Vol. 49, pp. 217-249.

Oh, S., and Haghani, A., (1996). "Formulation and Solution of a Multi-Commodity, Multi-Modal Network Flow Model for Disaster Relief Operations", *Transportation Research*, Vol. 30, pp. 231–250.

Oh, S., and Haghani, A., (1997). "Testing and Evaluation of a Multi-Commodity Multi-Modal Network Flow Model for Disaster Relief Management", *Journal of Advanced Transportation*, Vol. 31, pp. 249–282.

Ozdamar, L., and Demir, O., (2012). "A hierarchical clustering and routing procedure for large scale disaster relief logistics planning", *Transportation Research Part E*, Vol. 48, pp. 591–602.

Partovi, F.Y., (2015). "A model for the efficient assignment of emergency response employees", *International Journal of Management Science and Engineering Management*, Vol. 10, No. 1, pp. 33-40.

Peng, L., Tan, J., Lin, L., and Xu, D., (2019). "Understanding sustainable disaster mitigation of stakeholder engagement: Risk perception, trust in public institutions, and disaster insurance", *Sustainable Development*, Vol. 27, No. 5, pp. 885-897.

Rabbani, M., and Mousavi, Z., (2019). "Location of temporary depot after an earthquake based on robust optimization", *International Journal of Industrial Engineering & Production Research*, Vol. 30, No. 1, pp. 39-55.

Rabbani, M., Oladzad-Abbasabady, N., and Akbarian-Saravi, N., (2021). "Ambulance routing in disaster response considering variable patient condition: NSGA-II and MOPSO algorithms", *Journal of Industrial & Management Optimization*.

Rafie-Majd, Z., Pasandideh, S.H.R., and Naderi, B., (2018). "Modelling and solving the integrated inventory-location-routing problem in a multi-period and multi-perishable product supply chain with uncertainty: Lagrangian relaxation algorithm", *Computers & chemical engineering*, Vol. 109, pp. 9-22.

Saadatseresht, M., Mansourian, A., and Taleai, M., (2008). "Evacuation planning using multi objective evolutionary optimization approach", *European Journal of Operational Research*, Vol. 198, pp. 305-314.

Saffarian, M., Barzinpour, F., and Kazemi, S.M., (2017). "A Multi-Period Multi-Objective Location-routing Model for Relief Chain Management under Uncertainty", *International Journal of Supply and Operations Management*, Vol. 4, No. 4, pp. 298-317.

Sekar, S., Zheng, L., Ratliff, L.J., and Zhang, B., (2019). "Uncertainty in multicommodity routing networks: When does it help? ", *IEEE Transactions on Automatic Control*, Vol. 65, No. 11, pp. 4600-4615.

Sheu, J.B., (2007). "An emergency logistics distribution approach for quick response to urgent relief demand in disasters", *Transportation Research Part E: Logistics and Transportation Review*, Vol. 43, No. 6, pp. 687-709.

Sun, H., Wang, Y., and Xue, Y., (2021). "A bi-objective robust optimization model for disaster response planning under uncertainties", *Computers & Industrial Engineering*, Vol. 155, pp. 107213.

Tofighi, S., Torabi, S.A., and Mansouri, S.A., (2016). "Humanitarian logistics network design under mixed uncertainty", *European Journal of Operational Research*, Vol. 250, No.1, pp. 239-250.

Vahdani, B., Veysmoradi, D., Noori, F., and Mansour, F., (2018). "Two-stage multi-objective location-routing-inventory model for humanitarian logistics network design under uncertainty", *International journal of disaster risk reduction*, Vol. 27, pp. 290-306.

Vahdani, B., Veysmoradi, D., Noori, F., and Mansour, F., (2018). "Two-stage multi-objective location-routing-inventory model for humanitarian logistics network design under uncertainty", *International journal of disaster risk reduction*, Vol. 27, pp. 290-306.

Vahdani, B., Veysmoradi, D., Shekari, N., Mousavi, S.M., (2016). "Multi-objective, multi-period location-routing model to distribute relief after earthquake by considering emergency roadway repair", *Neural Computing and Applications*, pp. 1-20.

Wang Haijun , Du Lijing, Ma Shinhua., (2014). "Multi-objective open location-routing model with split delivery for optimized relief distribution in post-earthquake", *Transportation Research Part E:*

Logistics and Transportation Review, Vol. 69, pp. 160-179.

Wang, Q., and Nie, X., (2019). "A Stochastic Programming Model for Emergency Supply Planning Considering Traffic Congestion", *IISE Transactions*.

Yi, W., and Kumar, A., (2007). "Ant colony optimization for disaster relief operations", *Transportation Research Part E*, Vol. 43, pp. 660–672.

Yi, W., and Özdamar, L., (2007). "A dynamic logistics coordination model for evacuation and support in disaster response activities", *European Journal of Operational Research*, Vol. 179, No. 3, pp. 1177-1193.

Yueming, C., and Deyun, X, (2008). "Emergency Evacuation Model and algorithms", *Journal of Transportation Systems Engineering and Information Technology*, Vol. 8, pp. 96-100.

Zhu, C.F., Zhang, Z.K., and Wang, Q.R., (2019). "Path Choice of Emergency Logistics Based on Cumulative Prospect Theory", *Journal of Advanced Transportation*.

Zografos, K.G., and Androutsopoulos, K.N., (2008). "A decision support system for integrated hazardous materials routing and emergency response decisions", *Transportation Research Part C: Emerging Technologies*, Vol. 16, No. 6, pp. 684-703.